ELECTRIC ANALYSIS AND PORTFOLIO MODEL

APPENDIX H

PSE PUGET SOUND ENERGY

2023 Electric Progress Report

Contents

1. Introduction

Puget Sound Energy uses three models in our electric integrated resource planning: AURORA, PLEXOS, and a stochastic resource adequacy model. This appendix provides a detailed description of those models and our analyses.

We use AURORA in several ways:

1. To analyze the western power market to produce hourly electricity price forecasts of potential future market conditions and resource dispatch.
2. To create optimal portfolios and test them to evaluate PSE's long-term revenue requirements for the incremental portfolio and the risk of each portfolio.
3. To create simulations and distributions for various variables in the stochastic analysis.

PLEXOS estimates the cost savings due to sub-hour operation for new generic resources.

We use resource adequacy models in the following ways:

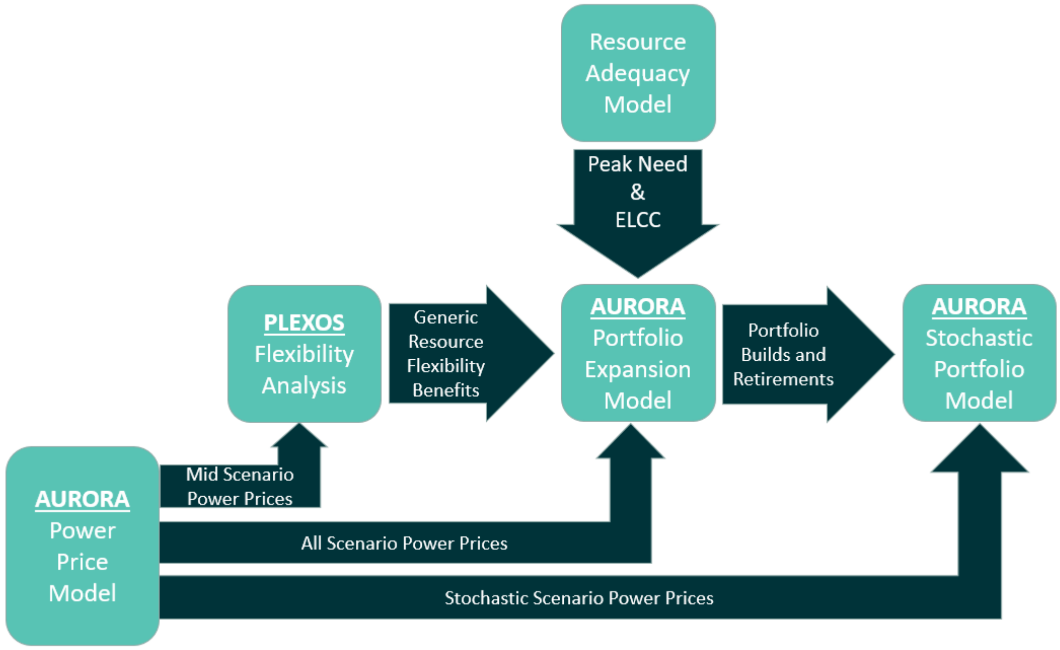
1. To quantify physical supply risks as PSE's portfolio of loads and resources evolves.
2. To establish peak load planning standards to determine PSE's capacity planning margin.
3. To quantify the peak capacity contribution of a renewable and energy-limited resource (effective load carrying capacity, or ELCC). The peak planning margin and ELCCs are inputs in AURORA for portfolio expansion modeling.

➔ A full description of resource adequacy modeling is in Chapter Seven: Resource Adequacy Analysis.

Figure H.1 demonstrates how the models are connected. We used the following steps to reach the least-cost portfolio for each scenario and sensitivity.

1. Create Mid-Columbia (Mid-C) power prices in AURORA for each electric price scenario.
2. Using AURORA's Mid Scenario Mid-C prices, run the flexibility analysis in PLEXOS to find the flexibility benefit for each generic supply-side resource.
3. Run a resource adequacy model to find the peak capacity need and ELCCs.
4. Using the electric price forecast, peak capacity need, ELCC, and flexibility benefit, run the portfolio optimization model in AURORA for new portfolio builds and retirements for each scenario and sensitivity portfolio.
5. Develop stochastic variables in AURORA around power prices, gas prices, hydro generation, wind generation, PSE loads, and thermal plant forced outages.

Figure H.1: Electric Analysis Methodology



2. AURORA Electric Price Model

We use Energy Exemplar's AURORA program to perform the electric price forecast process. AURORA is algebraic solver software used for decades in the utility industry to complete analyses and forecasts of the power system. The software allows us to perform comprehensive analyses and maintain a rigorous record of the data we used in the simulations.

We used the AURORA electric price model to forecast Mid-Columbia (Mid-C) wholesale electric prices over the planning horizon. The electric price model models all balancing authorities in the Western Electricity Coordinating Council (WECC).

➔ A full description of the electric price modeling is in Appendix G: Electric Price Models.

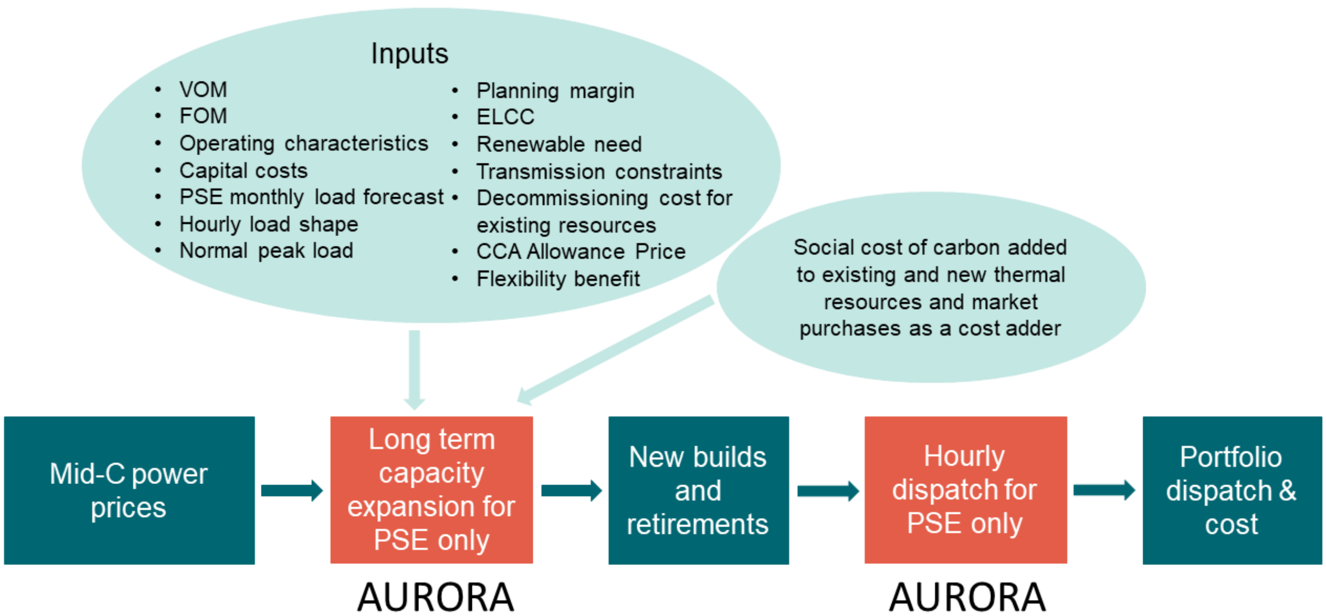
3. AURORA Portfolio Model

Puget Sound Energy’s electric portfolio model follows a four-step process:

1. We use a long-term capacity expansion (LTCE) model to forecast which resources to install and retire over a long-term planning horizon to keep pace with energy and peak needs and to meet the renewable requirement in the Clean Energy Transformation Act (CETA).
2. The LTCE run produces a set of resource builds and retirements, that includes the impact of the social cost of greenhouse gases.

3. The final set of builds and retirements is then passed to the standard zonal model in AURORA to simulate every hour of the 22 years for a complete dispatch.
4. The standard zonal hourly dispatch then produces the portfolio dispatch and cost.

Figure H.2: Aurora Portfolio Model



3.1. Long-term Capacity Expansion Model

We used a long-term capacity expansion model to forecast the installation and retirement of resources over a long period. Over the study period of an LTCE simulation, the model may retire existing resources and add new ones to the resource portfolio. We used AURORA to perform the LTCE modeling process.

We began the resource planning process by deploying the LTCE model to consider the current fleet of resources available to PSE, the options available to fill resource needs, and the planning margins required to fulfill our resource adequacy needs. The model used the demand forecast to calculate the resource need dynamically as it performed the simulation. The LTCE model has the discretion to optimize the additions and retirements of new resources based on resource needs, economic conditions, resource lifetime, and competitive procurement of new resources.

We established which new resources would be available to the model before we ran it. In consultation with interested parties, we identified potential new resources and compiled the relevant information to these resources, such as capital costs, variable costs, transmission needs, and output performance. We did not include contracts in the modeling process, since that information is not publicly available for transparency in the 2023 Electric Report.

3.2. Optimization Modeling

Optimization modeling finds the optimal minimum or maximum value of a specific relationship, called the objective function. The objective function in PSE's LTCE model is to minimize the revenue requirement of the total portfolio — the cost to operate the fleet of generating resources.

The revenue requirement at any given time is:

$$RR_t = \sum_{Resource} (Capital\ Costs_{Resource} + Fixed\ Costs_{Resource} + Variable\ Costs_{Resource}) + Contract\ Costs + DSR\ Costs + Market\ Purchases - Market\ Sales$$

Where t is the point in time, and RR_t is the revenue requirement at that time.

Over the entire study period, the model seeks to minimize the *Present Value* of the total revenue requirement, defined as:

$$PVRR = \sum_{t=1}^{T} RR_t * [\frac{1}{(1+r)^t} + \frac{1}{(1+r)^{20}}] * \sum Resource\ End\ Effects$$

Where PVRR is the present value of the Revenue Requirement over all time steps, and r is the inflation rate used.

To reach optimization, we use various methods, including linear programming, integer programming, and mixed-integer programming (MIP). AURORA uses MIP, a combination of integer and linear programming.

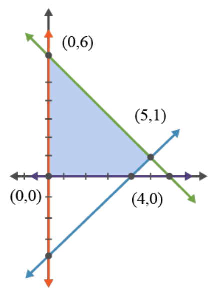
3.2.1. Linear Programming

Linear programming, or linear optimization, is a mathematical model represented by linear relationships and constraints. Linear programming optimizes a value constrained by a system of linear inequalities. In a power system model, these constraints arise from the capacities, costs, locations, transmission limits, and other attributes of resources. The constraints combine to form the boundaries of the solutions to the objective function. Figure H.3 demonstrates a basic example of linear programming, where an objective function C(x,y) is minimized and maximized

Figure H.3: Basic Example of Linear Programming

$$\textit{constraints:} \begin{cases} x + y \geq 6 \\ x - y \geq 4 \\ x \geq 0 \\ y \geq 0 \end{cases}$$

$$\textit{Objective Function:} \quad C = 2x + y$$



(0,0): $C = 2(0) + (0) = 0$ minimum

(0,6): $C = 2(0) + (6) = 6$

(5,1): $C = 2(5) + (1) = 11$ maximum

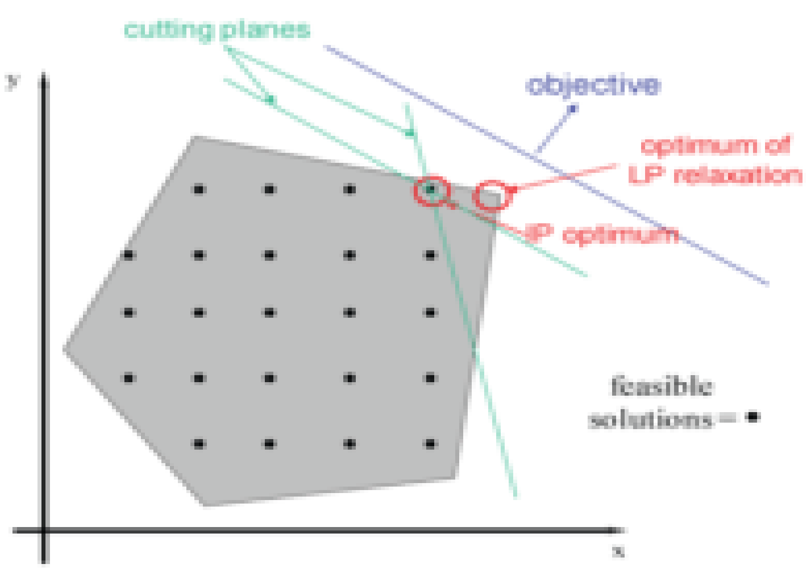
(4,0): $C = 2(4) + (0) = 8$

Calcworkshop.com

3.2.2. Integer Programming

Integer programming is another mathematical optimization method in which some or all the variables are restricted to integer values. The optimal solution may not be an integer value, but the limitation of the values in the model forces the optimization to produce a solution that accounts for these integer values. In the context of a utility, this may come in the form of having a discrete number of turbines that can be built, even though having a non-integer number of turbines will produce the optimal capacity. Figure H.4 shows an example of an integer programming problem. The optimal solution lies in the grey area, but only solutions represented by the black dots are valid.

Figure H.4: Visual Example of an Integer Programming Problem



3.2.3. Mixed Integer Programming

Mixed integer programming (MIP) combines linear and integer programming, where a subset of the variables and restrictions takes on an integer value. MIP methods are best suited for handling power system and utility models, as utilities' decisions and restraints are discrete (how many resources to build, resource lifetimes, how those resources connect) and non-discrete (the costs of resources, renewable profiles, emissions limitations).

In AURORA, MIP methods are the primary solver for completing all simulations, including the LTCE models. The software performs these methods iteratively and includes vast amounts of data, which makes the settings we use to run the model important in determining the runtime and precision of the solutions.

3.2.4. Iterative Solving

Optimization modeling can be deceptively simple when we break it down into sets of equations and solving methodologies. Limitations on computing power, the complexity of the model parameters, and vast amounts of data make a true solution impossible in many cases. To work around this, the LTCE model performs multiple iterations to converge on a satisfactory answer.

Given the complexity of the model, it does not produce the same results for each run. Over multiple iterations, AURORA compares each iteration's final portfolios and outputs with the previous attempt. If the most recent iteration reaches a certain threshold of similarity to the prior (as determined by the model settings) and has reached the minimum number of iterations, the program considers the solutions converged and provides it as the final output. If the model has reached the maximum number of iterations (also entered in the model settings), the last iteration will be considered the final output.

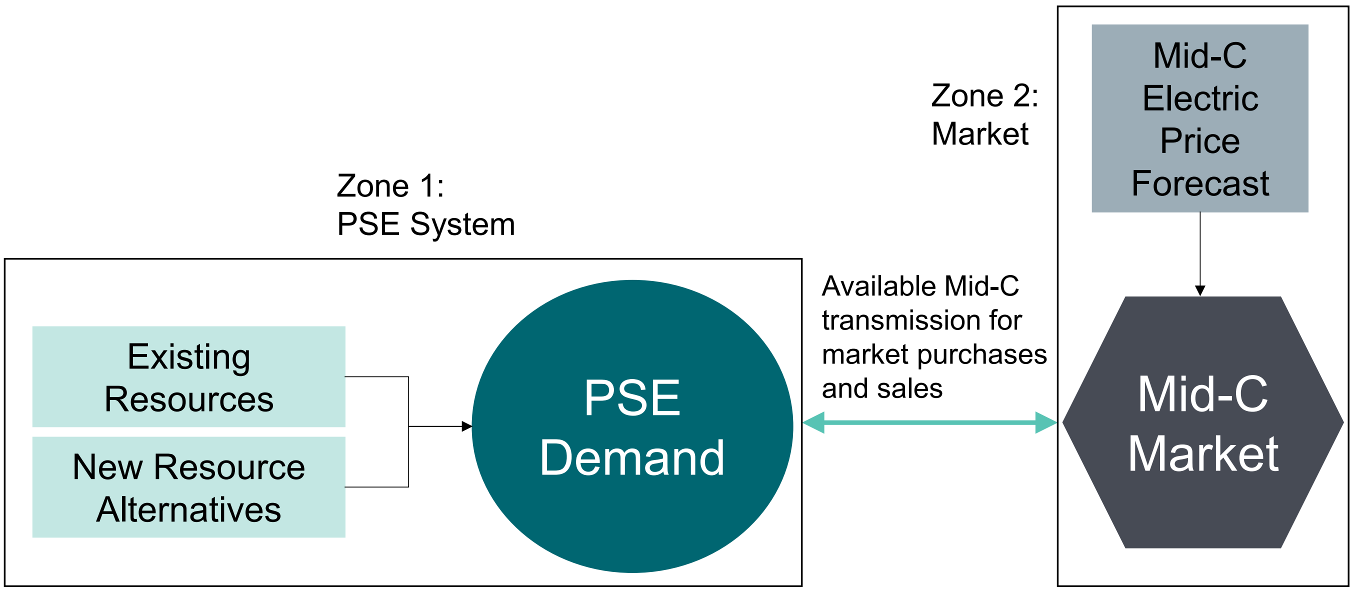
3.3. System Constraints

The solutions provided by optimizing the LTCE model seek to provide a path to meet PSE’s load and minimize the total price of the fleet. Without constraints, the LTCE optimization model selects the resource that produces the most power per resource dollar and builds as many as needed. This trivial solution provides no useful insight into how the utility should manage real resources. Constraints allow the model to find an effective solution.

3.3.1. Zonal Constraints

We divided the model into zones. The only transmission limits in the standard model are between zones, though we may add more transmission constraints for most simulations at the expense of runtime and computing power. The zonal model works best for generation optimization. We can use the nodal model for more detailed transmission optimization. Given the current constraints on technology and computing power, there is no integrated model for generation and transmission. Figure H.5 shows how this two-zone system operates in AURORA, where zones are represented as rectangular boxes, and the arrows between them represent transmission links.

Figure H.5: PSE's Two-zone System Set-up in AURORA



We operate a two-zone system for all simulations. This system limits the amounts of market purchases we can make at any given time due to transmission access to the Mid-C market hub.

3.3.2. Resource Constraints

We defined resources in the model by their constraints. A resource must be defined by constraints to make its behavior in the model match real-world operating conditions.

- **Resource Costs** — Generic resource costs give the model information about the capital costs in addition to variable and fixed operation and maintenance costs to make purchasing decisions.
- **Operating Characteristics** — Generic resource inputs contain information about when the resources can operate, including fuel costs, maintenance schedules, and renewable output profiles. These costs include transmission installation.
- **Availability** — Resources have a finite lifetime and a first available and last available year they can be installed as a resource. Resources also have scheduled and random maintenance or outage events that we include in the model.

3.3.3. Renewable Constraints

The model must meet all legal requirements. The most relevant renewable constraints PSE faces are related to the Renewable Portfolio Standard (RPS) and CETA.

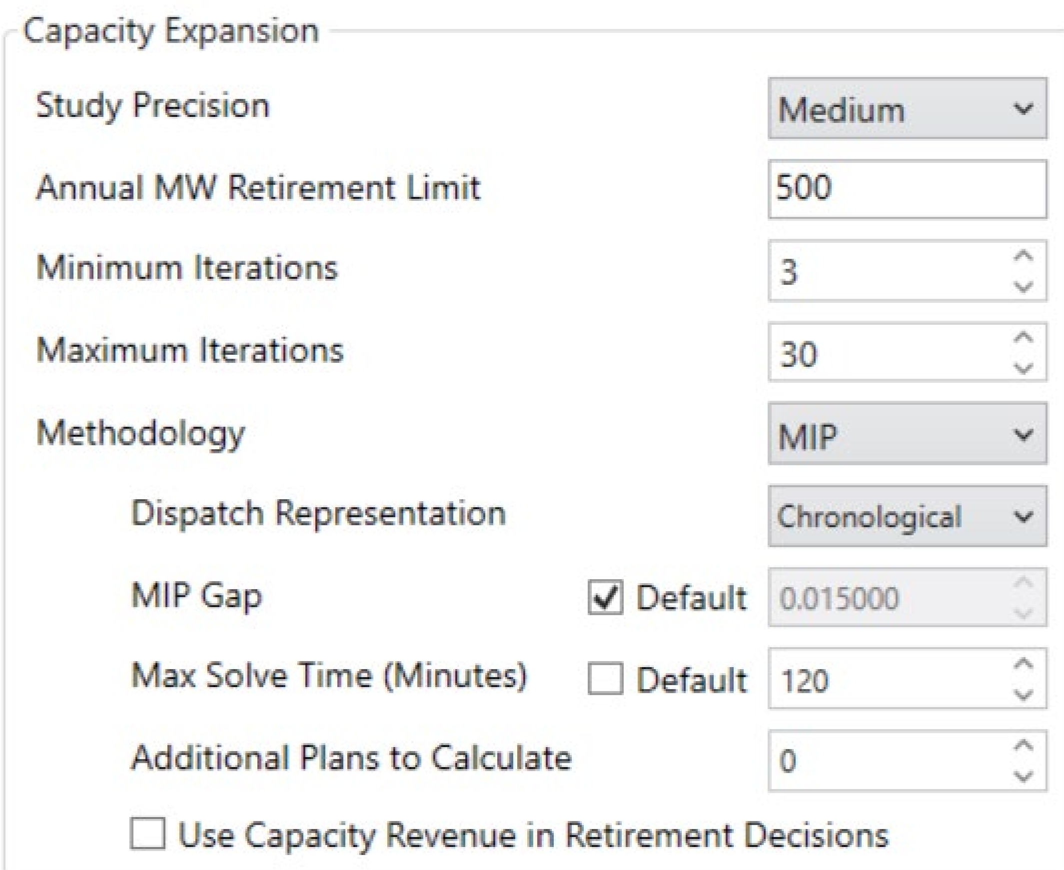
➔ See Chapter Five: Key Analytical Assumptions and Appendix D: Generic Resource Alternatives for more details on renewable constraints.

3.4. Model Settings

Our explanations for LTCE models rely heavily on the AURORA documentation provided by Energy Exemplar; we include relevant excerpts in the following section.

Before each LTCE model, we set parameters to determine how that simulation will run. The default parameters we used are in Figure H.6.

Figure H.6: Standard Aurora Parameters for PSE's LTCE Model



Note: These options are in the project file under Simulation Options → Long Term Capacity Expansion → Study Options → Long Term

3.4.1. Study Precision

During the iterative optimization process, the study precision controls when the model determines a solution is successfully converged. Instead of reaching one correct answer, the optimization process is multiple simulations that gradually converge on an optimized, stable answer given the model's assumptions. A visual representation of this process shows a model range gradually approaching an optimized solution. Users determine what is considered close enough to the absolute ideal answer by setting a percentage value for the study precision. Runtime limitations and computing power are the main drivers that limit the accuracy of a study.

The options for this setting include the following:

- High: Stops when the changes are less than 0.15 percent
- Medium: Stops when the changes are less than 0.55 percent
- Low: Stops when the changes are less than 2.5 percent

By experimenting with these settings, we determined the optimal setting is Medium, considering the tradeoff between runtime and precision.

3.4.2. Annual Megawatt Retirement Limit

The annual megawatt retirement limit restricts how much generating capacity can be economically retired in any given year. This setting does not include predetermined retirement dates, such as coal plant retirements, captured in the resources input data. We kept the default setting of 500 MW as a reasonable maximum for economic resource retirements to prevent outlier years where vast resources are retired.

3.4.3. Minimum Iterations

This setting specifies the minimum number of iterations that the simulation must complete. We set the minimum to three iterations to ensure that model decisions are checked.

3.4.4. Maximum Iterations

This setting specifies the maximum number of iterations that the simulation must complete. We set the maximum to 30 iterations to ensure the model's runtime does not become excessive. A simulation with more than 30 iterations will likely not converge on a usable solution.

3.4.5. Methodology

PSE uses the Mixed Integer Program (MIP) AURORA to perform the long-term capacity expansion model run.

4. Mixed Integer Program Methodology

The MIP methodology uses a Mixed Integer Program to evaluate resource build and retirement decisions. The MIP allows for a different representation of resources within the mode, leading to faster convergence times, more optimal (lower) system costs, and better handling of complex resource constraints. We employ the MIP methodology to take advantage of these benefits over traditional logic.

MIP-Specific Settings: Some settings within the MIP selection refine the performance of the MIP methods. We often use these settings at their default values, which are calculated based on the amount of data read into the AURORA input database for the simulation. The options are in the AURORA documentation and explained in Table H.1.

Table H.1: The MIP-specific Settings Used in the AURORA LTCE Model

Setting	Value Type	Definition
Dispatch Representation	Chronological	This methodology uses the dispatch of units in the chronological simulation (both costs and revenues) as the basis for the valuation of the build and retirement decisions. AURORA determines a net present value (NPV) for each candidate resource and existing resource available for retirement based on variable and fixed costs and energy, ancillary, and other revenue. Given the constraints, the method seeks to select the resources that provide the most value to the system. The formulation also includes internal constraints to limit the number of changes in system capacity between each iteration. These constraints are dynamically updated to help guide the solution to an optimal solution and promote convergence. We used this setting for the LTCE modeling process.
MIP Gap	Percent as a decimal value	This setting controls the precision level tolerance for the optimization. The default setting is generally recommended and will dynamically assign the MIP gap tolerance based on the study precision, objective setting, and potential problem size. When default is not selected, a value (generally close to zero) can be entered; the smaller the value, the harder the optimization works to find solutions.
Max Solve Time	Minutes	This setting controls the time limit for each LT MIP solution. Generally, using the default setting is recommended and will dynamically set the time limit based on the estimated difficulty of the problem (in most cases, about 30 minutes). If the default is not selected, the user can enter a value. If the time limit is reached, results may not be perfectly reproducible, so generally, a higher value is recommended.
Additional Plans to Calculate	Integer Value	When this value exceeds zero, AURORA will calculate additional plans after determining the final new build options and retirements. The program then adds a constraint to exclude the previous solutions, and then another MIP is formulated, and the solver returns its next best solution. The resource planning team sets this to zero.

5. Assumptions for all AURORA Models

The LTCE modeling process is a subset of the simulations we perform in AURORA. We keep most of these settings consistent across all models in AURORA, including the LTCE process. We may adjust sensitivities or simulations that are not converging properly. Table H.2 describes the settings we used in AURORA.

Table H.2: General Settings Used in all AURORA Models

Setting	Value Type	Definition
Economic Base Year	Year	The dollar year we set all currency to in the simulation. We used 2020 across all simulations through all IRP processes in AURORA for consistency, so we converted all inputs into 2020 dollars.

Setting	Value Type	Definition
Minimum Generation Backdown Penalty	Cost	Provides flexibility in modeling minimum generation segments and addresses linear programming solution infeasibility, which we can introduce due to hard minimum generation constraints. We set this value to $44.
Resource Dispatch Margin	Percentage	A value used to specify the margin over the cost of the resource required to operate that resource. We set this value to 0 percent.
Remove Penalty Adders from Pricing	Binary	When this option is selected, the model will adjust the zonal pricing by removing the effect of the non-commitment penalty on uncommitted resources and the minimum generation backdown penalty on committed or must-run resources. We used these penalty adders in the LP dispatch to honor commitment and must-run parameters; if this switch is selected, the model fixes resource output at the solved level before deriving zonal pricing without the direct effect of the adders. We selected this setting.
Include Variable O&M in Dispatch	Binary	We use this option to control the treatment of variable operation and maintenance (O&M) expenses. If selected, the variable O&M expenses are included in the dispatch decision of a resource. We selected this setting.
Include Emission Costs in Dispatch	Binary	This option allows the user to include the cost of emissions in the dispatch decision for resources. If not selected, the cost of emissions will not be included in the dispatch decision for resources. We selected this setting when modeling CO_2 price as a dispatch cost in select sensitivities.
Use Operating Reserves	Binary	This option determines whether the dispatch will recognize operating reserve requirements and identify a set of units for operating reserve purposes. When this option is selected, the model will choose a set of units (when possible) to meet the requirement. We selected this setting.
Use Price Caps	Binary	This option allows the user to apply price caps to specific zones in the database. If this option is selected, the model will apply specified price caps to the assigned zones. We selected this setting.

5.1. Resource Value Decisions

When solving for each time step of the LTCE model, AURORA considers the portfolio's needs and the resources available to fill those needs. The needs of the portfolio include capacity need, reserve margins, ELCC, and other relevant parameters that dictate the utility's ability to provide power. If there is a need, the model will select a subset of resources to fill that need.

At that time step in the program, each resource will undergo a small simulation to forecast how it will fare in the portfolio. This miniature forecast considers the operating life, capacity output, and scheduled availability of the resource. The model then considers resources that can best fulfill the needs of the portfolio on the merits of their costs.

Resource costs include the cost of capital to invest in the resource and fixed and variable O&M costs. Capital costs include the price of the property, physical equipment, transmission connections, and other investments required to acquire the physical resource. Fixed O&M costs include staffing and scheduled resource maintenance under normal conditions. Variable O&M costs include costs incurred by running the resource, such as fuel and maintenance costs accompanying use.

After we forecasted the costs of operating each resource, we compared them to find which had the least cost and served PSE's needs. The goal of the LTCE, an optimization model, is to provide a portfolio of resources that minimizes the cost of the portfolio.

6. Modeling Inputs

Several input assumptions are necessary to parameterize the model. These assumptions come from public and proprietary sources, and some we refined through our engagement process.

6.1. Forecasts

We cannot capture some attributes of the model in a single number or equation. Seasonal changes in weather, population behavior, and other trends that influence utility actions rely on highly time-dependent factors. We included a series of forecasts in the input assumptions to help provide these types of information into the model. Forecasts help direct overall trends of what will affect the utility in the future, such as demographic changes, gas prices, and environmental conditions. These forecasts are not perfect representations of the future, which is impossible to provide. However, they provide a layer of volatility that helps the model reflect real-world conditions.

Table H.3: Forecast Inputs and Sources

Input	Source	Description
Demand Forecast	Internal (see Chapter Six and Appendix F)	Energy and peak demand forecast for PSE territory over the IRP planning horizon.
Electric Price Forecast	Internal (see Appendix G)	The output of the AURORA electric power price model.
Natural Gas Price Forecast	Forward Marks prices, Wood Mackenzie (see Chapter Five)	A combination of the Forward Marks prices and Wood Mackenzie long-term price forecast.
Wind and Solar Generation	DNV	Solar and wind generation shapes dictate the performance of these renewable resources. Some forecasts are from existing PSE wind projects. Consultant DNV provides correlated wind and solar forecasts.

6.2. Resource Groups

Resources are split into two groups, existing and generic resources.

6.2.1. Existing Resources

We provided existing resources to the model as the base portfolio. Existing resources include those already in operation and those scheduled to be in the future. We also provided the model with scheduled maintenance and outage dates, performance metrics, and future retirement dates.

➔ See Appendix C: Existing Resource Inventory for more details of the existing resources modeled.

6.2.2. Generic Resources

Generic resources are the resources available to be added to the LTCE model. These resources represent real resources the utility may acquire in the future. Information about the generic resources includes the fuel used by the resources, costs, and availability. We also included transmission information based on the locations of the resources modeled.

➔ Details of the generic resources modeled are in Appendix D: Generic Resource Alternatives, and the numerical generic resource inputs in Appendix I: Electric Analysis Inputs and Results.

We simplified these resources to obtain representative samples of a particular resource group. For example, modeling every potential site where PSE may acquire a solar project would require prohibitive amounts of solar data from each location. To work around this issue, we used a predetermined site from different geographic regions to represent a solar resource in that area.

We developed the specific generic resource characteristics in partnership with IRP interested parties. As a result of feedback, we changed the costs of multiple resources to reflect more current price trends, and new resources were added, such as renewable and energy storage hybrid resources.

6.3. Capital Cost Calculations

The capital cost of a resource plays a large role in their consideration for acquisition by the model. Puget Sound Energy finances capital costs through debt and equity. The revenue requirement is the revenue the utility collects from ratepayers to cover operating expenses and the financing costs of the capital investment. The combined revenue requirement of all resources in the portfolio is the portfolio's total revenue requirement, the objective function the LTCE model seeks to minimize.

The revenue requirement is in the following equation:

$$\boxed{\text{Revenue Requirement} = \text{Rate Base} * \text{Rate of Return} + \text{Operating Costs}}$$

$$\text{Rate Base} = \text{Capital Investment}$$

$$\text{Rate of Return} = \text{Financing Costs (Set by the Commission)}$$

$$\text{Operating Costs} = \text{Fixed Operating Costs} + \text{Variable Operating Costs} + \text{Fuel} + \text{Depreciation} + \text{Taxes}$$

6.4. Social Cost of Greenhouse Gases

Per CETA requirements, we included the social cost of greenhouse gases (SCGHG) as an externality cost in the IRP process. We modeled the SCGHG as an externality cost added to the total cost of a given resource because CETA instructs utilities to use the SCGHG to make long-term and intermediate planning decisions. However, we also completed a portfolio sensitivity of the SCGHG as a variable dispatch cost based on requests from interested parties and as ordered by the Commission.

We revised how we applied the SCGHG for this 2023 Electric Report from the methodology presented in the 2021 IRP. For this report, we modeled the SCGHG as an externality cost adder with the following methodology:

1. We ran the LTCE model to determine portfolio-build decisions over the modeling timeframe. The LTCE model applied the SCGHG as a penalty to emitting resources (i.e., fossil-fuel resources) during each build decision and to market purchases.
    a. We applied the externality adder to emitting resources as follows:
        i. AURORA generates a dispatch forecast for the economic life of an emitting resource. The SCGHG does not impact this dispatch forecast to simulate real-world dispatch conditions.
        ii. The model summed the emissions of this dispatch forecast for the economic life of the emitting resource and applied the SCGHG to the total lifetime emissions.
        iii. The model then applied the lifetime SCGHG as an externality cost to the total lifetime cost of the resource.
        iv. The model based new build decisions on the total lifetime cost of the resource.
    b. We applied the externality cost to market purchases as follows:
        i. Modeled unspecified market purchases with an emission rate of 0.437 metric tons of CO_2eq per MWh.[1]
        ii. Multiplied the annual social cost of greenhouse gases by this emission rate and applied it as a hurdle rate added to the cost of market purchases in the LTCE model.
2. The LTCE model creates a portfolio of new builds and retirements. Since the LTCE runs through many simulations, we used a sampling method to decrease run time; so, in the final step, we passed the portfolio to the hourly dispatch model, which can model dispatch decisions at a much higher time resolution. The hourly dispatch model cannot make build decisions but more accurately assesses total portfolio cost to ratepayers. Since the SCGHG is not a cost passed to ratepayers, we did not include the SCGHG in the hourly dispatch modeling step.

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In the 2021 IRP, we calculated the fixed cost adder based on a separate AURORA dispatch model run to estimate the emissions expected for each emitting resource type. We then applied the fixed cost adder statically to subsequent simulations. In this progress report, we used the AURORA dispatch model's improved functionality to apply the SCGHG to emitting resources dynamically. In the revised methodology, AURORA dispatches emitting resources not subject to the SCGHG, then applies the SCGHG for all emissions over the resource's lifetime to the total cost of the resource when calculating the resource value for addition and retirement decisions. The 2023 model's SCGHG accounting is a marked improvement from the 2021 IRP methodology because the new accounting method more accurately represents the emissions of resources which may vary by simulation due to input changes or variation in the resource mix.

We applied the SCGHG to market purchases consistently in this report and the 2021 IRP — we added a hurdle rate to the cost of market purchases that reflects the unspecified market purchase emission rate. Modeling the SCGHG on market purchases as a hurdle rate impacts the dispatch of market purchases in the modeling framework. Reflecting the SCGHG as a dispatch cost on market purchases and as an externality cost to emitting resources introduces bias against market purchases into the model. We identified this bias late in the 2023 Electric Report modeling process and are actively working to identify a solution for future IRP cycles.

Interested parties requested that we include the SCGHG as a dispatch cost on emitting resources. We implemented this request as follows in Sensitivity 15:

1. Run a long-term capacity expansion (LTCE) model to determine portfolio-build decisions over the modeling timeframe. Apply the SCGHG in the LTCE model as a penalty to emitting resources during each build decision as a dispatch cost, which means the total energy produced by the resource decreased due to the higher dispatch cost.
2. The LTCE model results in a portfolio of new builds and retirements. Since the LTCE runs through many simulations, use a sampling method to decrease run time, then pass the portfolio to the hourly dispatch model, which can model dispatch decisions at a much higher resolution. The hourly dispatch model cannot make build decisions but will more accurately assess total portfolio cost to ratepayers. We omitted the SCGHG in the hourly dispatch modeling step.

➔ See Chapter Eight: Electric Analysis for more information on sensitivity 15.

6.5. Climate Commitment Act

The Climate Commitment Act (CCA) is a cap-and-invest bill that places a declining limit on the quantity of greenhouse gas emissions generated within Washington State and establishes a marketplace to trade allowances representing permitted emissions. The resulting market creates an opportunity cost for emitting greenhouse gases.

We added an emission price to greenhouse gas emissions in the electric price forecast model for emitting resources within Washington State to model this opportunity cost. We only added the emission price to Washington State emitting resources to ensure the model reflects any change in dispatch without impacting that of resources outside

Washington State not subject to the rule. To accurately reflect all costs imposed by the CCA, we added a hurdle rate on transmission market purchases to the PSE portfolio model to account for unspecified market purchases using the CCA price forecast at the unspecified market emission rate 0.437 metric tons of CO2eq per MWh.[2]

We modeled the CCA allowance as a variable cost on both emitting resources and market purchases. This method means the impact of the CCA allowance price will impact the dispatch of these resources, reducing the amount of energy generated by these resources. We included the CCA allowance prices in the LTCE and hourly dispatch models because it is a direct cost on emitting resources and market purchases.

➔ See Chapter Five: Key Analytical Assumptions and Appendix I: Electric Analysis Inputs and Results for additional information on the CCA allowance price.

7. Embedding Equity

This section describes the methods we used in the 2023 Electric Report to quantify how different portfolios can improve equitable outcomes for named communities.

We analyzed these benefits outside the AURORA model with an Excel-based analysis called the portfolio benefit analysis. The AURORA program is a production cost model that seeks to identify the lowest-cost portfolio given constraints. Currently, elements of an equitable portfolio are difficult to translate into cost values; therefore, AURORA is ill-equipped to incorporate equity into its solution. Consequently, we developed the portfolio benefit analysis to obtain a relative measure of benefits for each portfolio analyzed as part of the planning process.

➔ We discuss the results in Chapter Eight: Electric Analysis. Appendix I: Electric Analysis Inputs and Results is the Excel workbook that contains the data and the numerical analysis results.

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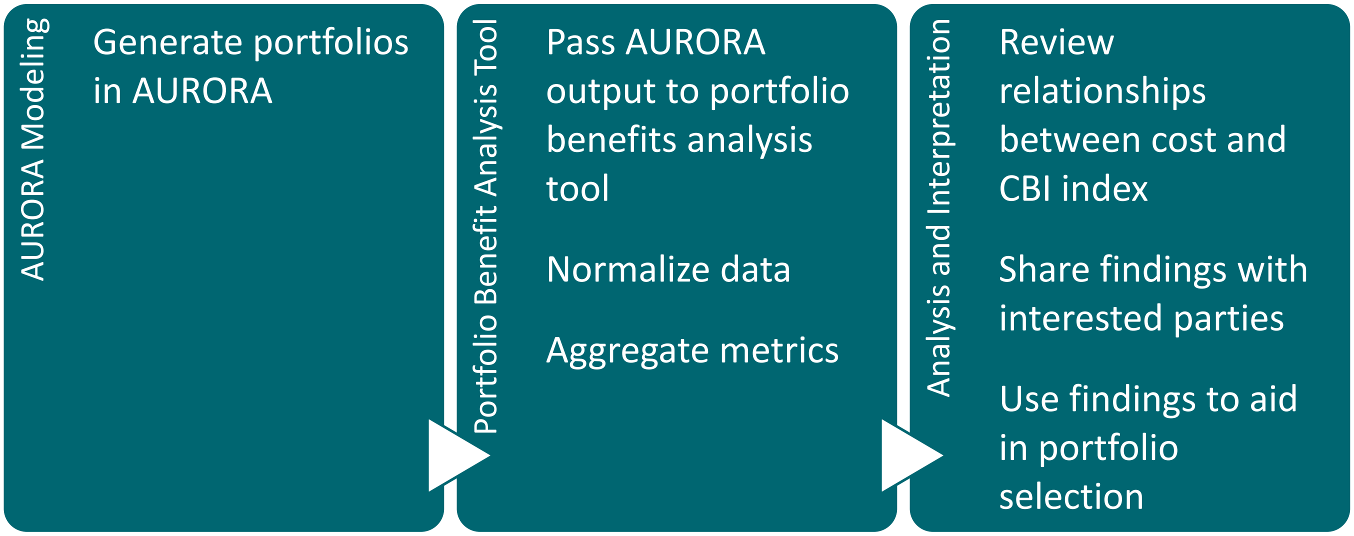
Figure H.7: Elements of the Portfolio Benefit Analysis Process



The portfolio benefit analysis measures the number of customer benefits of each portfolio modeled. We use select metrics from the AURORA output to represent the Customer Benefit Indicators (CBIs) we developed as part of the 2021 Clean Energy Implementation Plan (CEIP), working collaboratively with our Equity Advisory Group (EAG) and customers.

The portfolio benefit analysis measures potential equity-related benefits to customers within a given portfolio and the tradeoff between those benefits and overall cost. We evaluated these benefits using quantitative customer benefit indicators (CBIs) and their metrics. Customer benefit indicators are quantitative and qualitative attributes we developed for the 2021 CEIP in collaboration with our Equity Advisory Group (EAG) and interested parties. These CBIs represent some of the focus areas in CETA related to equity, including energy and non-energy benefits, resiliency, environment, and public health.

For this 2023 Electric Report, we evaluated each portfolio using a subset of the CBIs proposed in the 2021 Clean Energy Implementation Plan, which as of this date, is still pending Washington Utilities and Transportation Commission (Commission) approval. We selected the subset of CBIs based on whether the AURORA model could quantitatively evaluate them, i.e., AURORA already had a comparable metric.

We describe the elements of the portfolio benefit analysis in the following sections.

7.1. Modeling

The first step in the portfolio benefits analysis is to generate portfolios to review. Portfolios are a collection of generating resources PSE could use to serve electrical demand. First, we create a reference portfolio that represents the lowest-cost portfolio to satisfy the base modeling assumptions. Then we generate a variety of portfolios to represent a range of economic conditions, resource assumptions, and environmental regulations to learn how those changes impact the resource mix and cost of the portfolio.

➔ We describe the AURORA portfolio modeling throughout this appendix and provide results for each portfolio in Chapter Eight: Electric Analysis.

7.2. Data Collection

Following the modeling process, we collected targeted data from the AURORA output for each portfolio. We can measure many CBIs directly from this data, such as emissions and portfolio cost. However, AURORA does not generate job, customer, or participant data. The portfolio benefit analysis combines the technology-specific capacity built over the 22-year planning period with additional data to generate meaningful metrics to evaluate these CBIs.

- **Jobs**: The portfolio benefit analysis uses a technology-specific job per megawatt (MW) metric to convert the technology-specific capacity AURORA provides into a total number of jobs created for a given portfolio. The jobs/MW metric combines the 2022 U.S Energy and Employment Jobs Report[3] data with the technology-specific total capacity operating nationally, sourced from the 2022 Early Release EIA Forms 860[4] and 861[5].
- **Demand Response and Distributed Energy Resources (DER) participation**: We show the number of expected participants in demand response programs in PSE's 2022 Conservation Potential and Demand Response Assessments that we produced for this 2023 Electric Report and provided in Appendix E. Historic DER participation data is from the 2022 EIA Form 861M[6].

Table H.4 summarizes the CBIs, associated metrics, and data sources we evaluated in the portfolio benefit analysis tool.

Table H.4: Metrics and Data Sources in the Portfolio Benefit Analysis

CBI	Measurement Metric (Unit)	Data Source
Reduced greenhouse gas emissions	CO_2 (short tons)	AURORA output
Improved affordability of clean energy	Portfolio cost ($)	AURORA output
Improved outdoor air quality	Sulfur oxides (Sox), nitrogen oxides (Nox), and particulate matter (PM) (short tons)	AURORA output
Increased participation in Energy Efficiency, Distributed Energy Resources, and Demand Response programs	Customer in each program (count)	AURORA output PSE's 2022 Conservation Potential Assessment and Demand Response Assessment 2021 Early Release EIA Form 861M
Increase in the number of jobs	Jobs generated (count)	2022 U.S Energy and Employment Jobs Report and

3 https://www.energy.gov/sites/default/files/2022-06/USEER%202022%20National%20Report_1.pdf
4 https://www.eia.gov/electricity/data/eia860/
5 https://www.eia.gov/electricity/data/eia861/
6 https://www.eia.gov/electricity/data/eia861m/

CBI	Measurement Metric (Unit)	Data Source
		2021 Early Release and EIA Forms 860 and 861
Improved access to reliable, clean energy	Customers with access to storage resources (count)	AURORA output 2021 Early Release EIA Form 861M
Reduction in peak demand	Peak reduction through Demand Response (MW)	AURORA output

7.3. Normalization

The portfolio benefit analysis normalizes all metrics to 1) allow comparison between metrics with different units, such as emissions and job data, and 2) create an overall CBI index to compare portfolios and sensitivities. The portfolio benefit analysis normalizes metrics using a modified z-score, where we set the reference portfolio to equal zero, and each sensitivity converts to an index measuring the number of standard deviations from the reference portfolio. All positive indices indicate a more favorable CBI outcome than the reference portfolio.

7.4. Aggregation

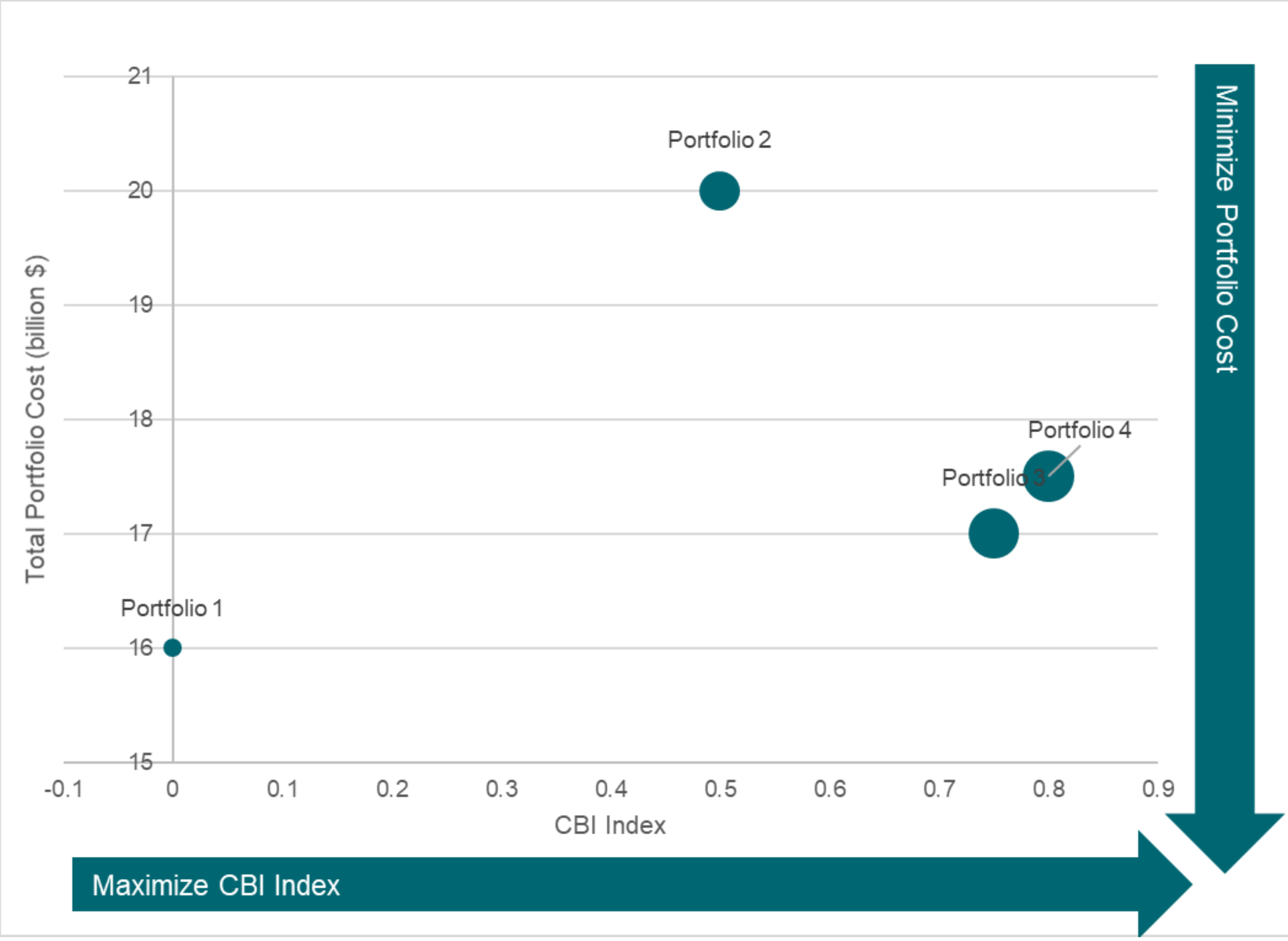
Following normalization, the portfolio benefit analysis combines all CBI indices into a single index for the portfolio using the arithmetic mean. The overall CBI index provides a single value representing the relative quantity of benefits each portfolio provides and facilitates direct comparison between the various portfolios.

7.5. Analysis

We plotted the overall index for each portfolio against the total portfolio cost. This plot illustrates the tradeoff between increasing CBI value and cost. Compared to the reference portfolio, the most efficient portfolios have the greatest CBI indices with minimal increase in portfolio cost.

Figure H.8 illustrates an example scenario where we analyzed four portfolios. We plotted the reference portfolio, Portfolio 1, near the origin. Portfolio 2 demonstrates an inefficient portfolio, where a moderate increase in the CBI index costs four billion dollars more than the reference portfolio. Conversely, Portfolios 3 and 4 illustrate more efficient portfolios, where the relative increase in the CBI index costs an additional one or one and a half billion dollars, respectively. The most efficient portfolios are near the bottom, right side of the plot. The point's radius illustrates the second indication of efficiency; the larger points indicate increased CBI value per dollar spent.

Figure H.8: Sample Portfolio Benefit Analysis Comparison Plot



7.6. Interpretation

Next, we further reviewed the details of the most efficient portfolios, considering the resource mix and the real-world applicability. In the example illustrated in Figure H.6, the relationship between Portfolios 3 and 4 shows a tradeoff between cost and CBI value, often referred to as an efficiency frontier. Portfolio 3 offers a lower cost, while Portfolio 4 offers a higher CBI value. In this case, we must review portfolio-build decisions and consider additional factors.

For example, if Portfolio 4 requires 1,000 MW of distributed rooftop solar installed by 2030, but this is infeasible due to a supply chain shortage and a deficit in interested and available participants, Portfolio 4 would not be selected as the preferred portfolio, even though it has the highest CBI index. Similarly, we would not automatically choose a sensitivity based on cost alone.

After reviewing an initial group of portfolios, we shared initial conclusions with internal and external parties to gain additional perspective on the candidate portfolios. The feedback from interested parties included recommendations that we analyze different portfolios that included or excluded specific resource types. We analyzed these other portfolios and added the results to the portfolio benefit analysis.

Because the portfolio benefit analysis uses a modified z-score methodology to convert raw data into an index, the index is subject to change by introducing new portfolios. Therefore, to minimize user bias, once a portfolio is analyzed, it will remain within the portfolio benefit analysis, even if we deem it inefficient or infeasible.

Further interpretation of the initial and new portfolios together provides context for selecting the preferred portfolio from a selection of candidate portfolios.

8. Financial Assumptions

As the portfolio modeling process takes place over a long-term timeline, we must make assumptions about the financial system the resources will operate in.

8.1. Tax Credit Assumptions

Before the Inflation Reduction Act (IRA), Production Tax Credit (PTC) and Investment Tax Credit (ITC) values were based on the start of construction with a four-year window to complete a qualifying project. We phased down the PTC and ITC, where PTC was set to expire in 2022, and ITC was ramped down to 10 percent indefinitely. The ramp-down created uneven investment decisions to capture the most value for the tax credits. The tax credits were technology specific: PTC for wind and ITC for standalone solar and solar paired with storage.

The IRA extended the PTC to 100 percent value and the ITC back to the maximum 30 percent value. The IRA now makes the PTC and ITC technology neutral. The IRA expanded the tax credits to include standalone storage and advanced nuclear.

There is a bonus incentive that may allow businesses to achieve more project-specific tax credit incentives. The additional credits are as follows:

- Ten percent for domestic consent
- Ten percent energy community credit
- Ten to twenty percent of low-income communities' projects under 5MW (ITC only)

The PTC provides tax credits based on a project's first 10 years of output. The current PTC rate is $26/MWh and is adjusted annually for inflation. Solar projects are now eligible for PTC, which is more economical than the ITC from our analysis.

We apply the 30 percent ITC to investments in a qualifying project. The ITC provides a large benefit for standalone storage, now providing a 30 percent discount on capital costs.

8.2. Discount Rate

We used the pre-tax weighted average cost of capital (WACC) from the 2019 General Rate Case of 6.8 percent nominal.

8.3. Inflation Rate

Unless otherwise noted, we used a 2.5 percent escalation for all assumptions. This is the long-run average inflation rate the AURORA model uses.

8.4. Transmission Inflation Rate

In 1996, the BPA rate was $1.000 per kW per year, and the estimated total rate in 2015 was $1.798 per kW per year. Using the compounded average growth rate (CAGR) of BPA Point-to-Point (PTP) transmission service (including fixed ancillary service Scheduling Control and Dispatch) from 1996 to 2015, we estimated the nominal CAGR inflation rate to be 3.05 percent annually.

8.5. Gas Transport Inflation Rate

Natural gas pipeline rates are not updated often, and recent history indicates the rates are 0 percent. We assumed zero inflation on pipeline rates because our major pipelines have declining rate bases, and we will incrementally price major expansions. We expect growth in service costs from operating costs and maintenance capital additions to be offset by declines due to depreciation.

8.6. Transmission and Distribution Costs

The transmission and distribution (T&D) benefit, also known as an avoided cost, is a benefit added to resources that reduce the need to develop new transmission and distribution lines. The T&D benefit is our forward-looking estimate of T&D system costs under a scenario where electrification requirements and electric vehicles drive substantial electric load growth. Studies of the electric delivery system identified capacity constraints on the transmission lines, substations, and distribution lines that serve PSE customers from increased load growth due to electrification and electric vehicle adoption. We used the estimated cost for the infrastructure upgrades required to mitigate these capacity constraints and the total capacity gained from these upgrades to calculate the benefit value. The 2023 Electric Report included a T&D benefit of $74.70/kW-year for DER batteries. The model forecasted this estimated $74.70/kW-year based on our different transmission and delivery system needs under such a scenario. This increase is a significant change from the $12.93/kW-year we used in the 2021 IRP which used backward-looking metrics instead of the revised forward-looking scenario described above.

9. AURORA Stochastic Risk Model

A deterministic analysis is a type of analysis where all assumptions remain static. Given the same set of inputs, a deterministic model will produce the same outputs. In PSE's resource planning process, the deterministic analysis identifies the least-cost mix of demand-side and supply-side resources that will meet need, given the set of static assumptions defined in the scenario or sensitivity. In this report, PSE modeled additional deterministic sensitivities, which allowed us to evaluate a broad range of resource options and associated costs and risks. The sensitivity analysis is a type of risk analysis. We can isolate how one variable changes the portfolio builds and costs by varying one parameter.

Stochastic risk analysis deliberately varies the static inputs to a deterministic analysis to test how a portfolio developed in the deterministic analysis performs concerning cost and risk across a wide range of possible future power prices, natural gas prices, hydro generation, wind generation, loads, and plant forced outages. By simulating the same portfolio under different conditions, we can gather more information about how a portfolio will perform in an uncertain future. We completed the stochastic portfolio analysis in AURORA.

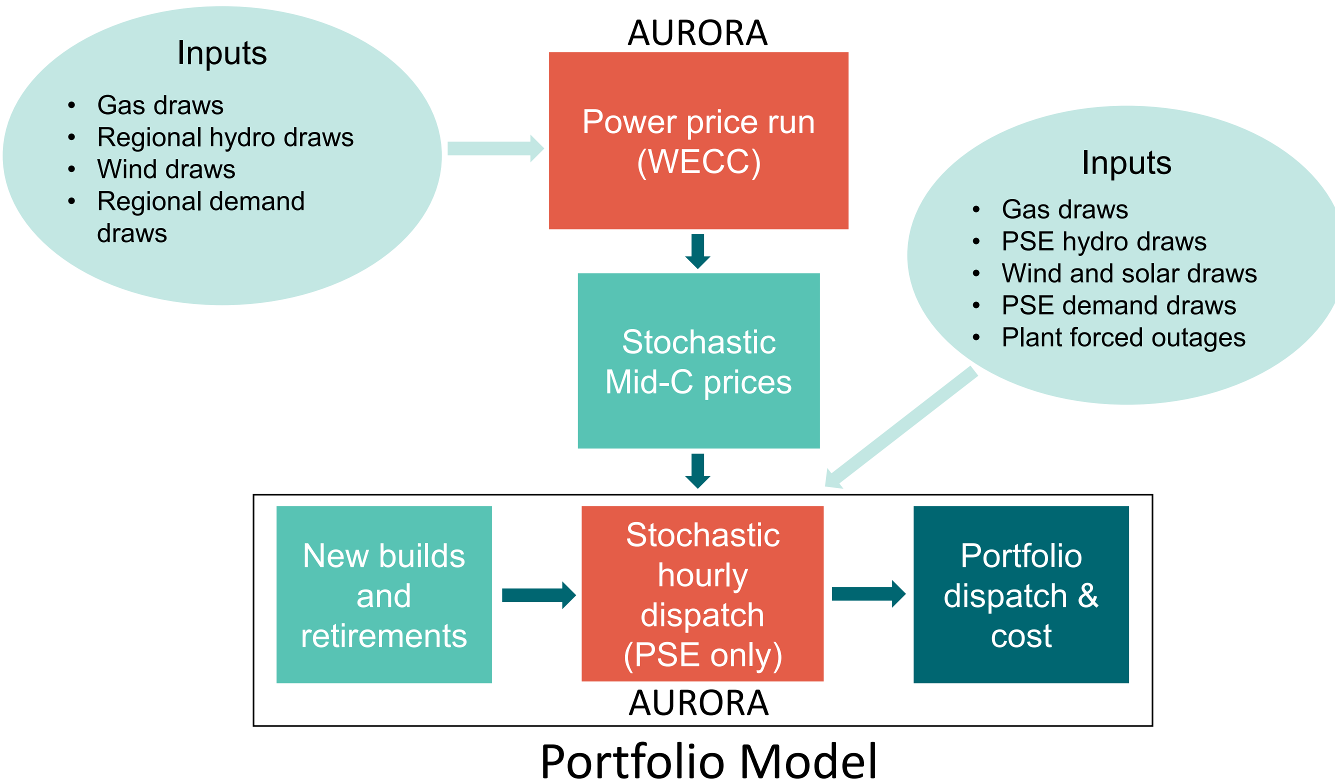
The stochastic modeling process aims to understand the risks of alternative portfolios in terms of costs and revenue requirements. This process involves identifying and characterizing the likelihood of different forecasts, such as high prices, low hydroelectric, and the adverse impacts of their occurrence for any given portfolio.

The modeling process used to develop the stochastic inputs is a Monte Carlo approach. Monte Carlo simulations generate a distribution of resource energy outputs (dispatched to prices and must-take), costs, and revenues from AURORA. The stochastic inputs considered in this report are electric power prices at the Mid-Columbia market hub, natural gas prices for the Sumas and Stanfield hubs, PSE loads, hydropower generation, wind generation, solar generation, and thermal plant forced outages. This section describes how PSE developed these stochastic inputs.

9.1. Development of Stochastic Model Inputs

A key goal in the stochastic model is to capture the relationships of major drivers of risks with the stochastic variables in a systematic way. One of these relationships, for example, is the correlation of variations in electric power prices with variations in natural gas prices contemporaneously or with a lag. Figure H.9 shows the key drivers we used to develop these stochastic inputs. Long-term economic conditions and energy markets determine the variability in the stochastic variables.

Figure H.9: Major Components of the Stochastic Modeling Process



Our stochastic model used the following process to simulate 310 futures of portfolio dispatch and cost:

1. Generate electric price draws. Like the deterministic wholesale price forecast, we used the AURORA model to simulate resource dispatch to meet demand and various system constraints. We vary regional demand, gas prices, and hydro and wind generation to create electric price draws. We use the price forecast for the Mid-C zone as the wholesale market price in the portfolio model.
2. Pull the electric and natural gas price draws generated in the first step into the hourly portfolio dispatch model.
3. Run the different portfolios drawn from the deterministic scenario and sensitivity portfolio through 310 draws that model varying power prices, gas prices, hydro, wind, and solar generation, load forecasts (energy and peak), and plant forced outages. From this analysis, we can observe how robust or risky the portfolio may be and where significant differences occur when we analyze risk.

9.2. Stochastic Electric Price Forecast

We use AURORA, a production cost model that utilizes electric market fundamentals to generate electric price draws. AURORA offers a Monte Carlo Risk capability that allows users to apply uncertainty to a selection of input variables. Users can add the variability of input assumptions into the model as an external data source, or AURORA can generate samples based on user statistics on a critical driver or input variable.

➔ Appendix G : Electric Price Models describes the methods and assumptions used to generate the stochastic electric price forecast and the simulation results.

9.3. Stochastic Portfolio Model

We use AURORA for stochastic portfolio modeling and apply a pre-defined iteration set to modify the input data in the model. We take the portfolios (drawn from the deterministic scenario and sensitivity portfolios) and run them through 310 draws that model varying power prices, gas prices, hydroelectric generation, wind generation, solar generation, load forecasts (energy and peak), and plant-forced outages. This section describes the model input assumptions we varied to generate the portfolio dispatch and cost.

9.4. Electric and Natural Gas Prices

The model packaged each completed set of power prices with gas prices and the assumed hydroelectric inputs when it generated the power price forecast. This bundle of power, gas prices, and hydroelectric conditions are input to the stochastic portfolio model. By packaging the power price, gas price, and hydroelectric year, the model preserved the relationships between gas prices and Mid-C prices and between hydro and power prices. Since there are only 90 draws generated from the stochastic electric price forecast, we sampled the electric price and natural gas uniformly to generate 310 draws.

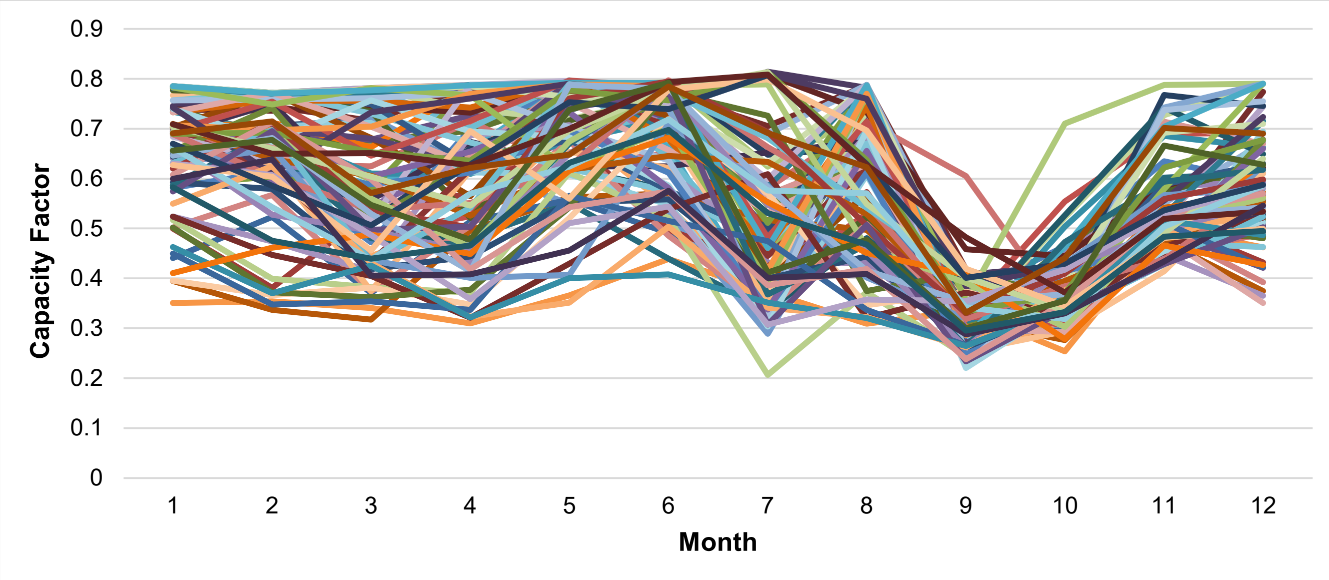
➔ Appendix G: Electric Price Models describes electric and natural gas price inputs.

9.5. Hydroelectric Variability

We use the same climate change hydroelectric data described in Appendix G: Electric Price Models for the stochastic electric price model. It is also the same hydroelectric data the Northwest Power and Conservation Council used for its 2021 Power Plan. Staying consistent with the other entities is essential since we all model the same hydropower projects.

Puget Sound Energy does not significantly depend on owned or contracted hydroelectric resources, so variations have a smaller effect on our ability to meet demand. The hydroelectric variations have a larger impact on the market for short-term purchases, as captured in the market risk assessment. The hydroelectric output of all 90 hydroelectric years is in Figure H.10. We uniformly sampled the 90 hydroelectric draws to generate 310 draws.

Figure H.10: Monthly Average Capacity Factor for 5 Mid-C Hydro Projects, 90 Draws



9.6. Electric Demand

The demand forecasts assume economic, demographic, temperature, electric vehicle, and model uncertainties to generate the set of stochastic electric demand forecasts.

The model derives the high and low monthly and annual demand forecasts from the distribution of these stochastic forecasts.

➔ Chapter Six: Demand Forecast and Appendix F: Demand Forecasting Models fully explain the stochastic demand forecasts.

9.7. Wind and Solar Variability

Consultant DNV generated wind and solar shapes to use in this Electric Report. On behalf of PSE, DNV used location information with the turbine model and power data as inputs to a stochastic model. The stochastic model generated 1,000 stochastic time series to represent the net capacity factor of a given wind or solar project for each site over the 22-year planning period. This methodology maintained daily, seasonal, and annual cycles from the original data. The stochastic model also maintained spatial coherency of weather, generation, and system load to preserve the relationships of projects across a region. DNV then randomly selected a sample of 250 annual hourly draws for each site, verified that the data represented the total distribution, and provided the data to PSE for modeling purposes.

We used the 250 wind and solar draws in the stochastic analysis. After the model selected each wind or solar draw once, it uniformly resampled the data to fill the remaining draws needed to generate 310 stochastic iterations.

➔ Appendix D: Generic Resource Alternatives contains a complete description of the wind and solar curves.

9.8. Forced Outage Rates

AURORA uses the frequency duration method, assigning each thermal plant a forced outage rate. This value is the percentage of hours in a year where the thermal plant cannot produce power due to unforeseen outages and equipment failure. This value does not include scheduled maintenance. In the stochastic modeling process, the model used the forced outage rate to randomly disable thermal generating plants, subject to the resource's minimum downtime and other maintenance characteristics. Over a stochastic iteration, the total time of the forced outage events will converge on the forced outage rate. This outage method option allows units to fail or return to service at any time step within the simulation, not just at the beginning of a month or a day. The frequency and duration method assumes units are either fully available or out of service.

9.9. Stochastic Portfolio Results

We tested the reference and preferred portfolios (sensitivity 11 B2) with the stochastic portfolio analysis.

➔ Stochastic results are in Chapter Eight: Electric Analysis, and the data is in Appendix I: Electric Analysis Inputs and Results.

10. PLEXOS Flexibility Analysis Model

Developed by Energy Exemplar, PLEXOS is an advanced production cost modeling tool we use for its capability to represent real-world, short-term operational decision cycles. This sophisticated platform allows us to appropriately model cost and reliability impacts associated with subhourly forecast uncertainty and renewable resource intermittency. Our flexibility analysis model provides for studies of interactions within our Balancing Authority Area (BAA), which designates the collection of electrical resources PSE controls and uses to balance supply and demand in real time. The BAA is different from our electric service area because some resources, such as wind and solar generators, could be physically located in the service area of another utility but are still considered part of PSE's BAA obligations. Our flexibility analysis model provides critical insights into PSE's capabilities to integrate renewable resources into our BAA and understand the benefits of additional flexible generation resources beyond capacity and energy value.

To appropriately reflect conditions on a subhourly basis, we must develop the PLEXOS model to reflect cycle-specific decisions and recourse actions carefully. We must make some decisions based on their decision cycle, such as a day-ahead block transaction at Mid-C occurring in a day-ahead model. However, the energy schedule of generators in a day-ahead model is generally not required to remain constant across the studied day. Modeling these decisions, which we must fix in models of later decision cycles and allowing recourse actions to occur as uncertainty resolves, such as peaker commitments, are critical to reflect the subhourly flexibility of PSE's system accurately. Currently, our flexibility analysis model studies scheduled system impacts down to 15-minute segments.

The starting point of this analysis is a base portfolio comprised of PSE's existing resources scheduled to be operational through 2029, plus sufficient firm capacity, so the model is not resource inadequate, on an hourly timeframe, based on the results of the Resource Adequacy study. However, the model fixes firm capacity hourly, so it does not affect the analysis of subhourly flexibility. In this way, the model design prevents insufficient capacity or energy from affecting the results, with a resource-deficient starting position and no knowledge of the portfolio in 2029. When the model adds new resources, the firm capacity available to make the hourly model resource sufficient is adjusted down, so the total peak capacity in the model matches the peak need in 2029.

We ran the base case, what is presently known about our portfolio through the year 2029, and pivot cases, which are each the base case portfolio plus the addition of one new resource, through the simulation phases. The model then calculates the subhourly dispatch cost associated with each case. A difference in the subhourly costs of each pivot case against the base case is the flexibility benefit associated with the resource decision. This benefit is the cost difference of the study year divided by resource nameplate rating and determines a benefit per year ($/kW-year). As part of the IRP's decision framework, our flexibility analysis model uses subhourly benefits associated with new resource pivots calculated and made available to the LTCE model in AURORA by applying the flexibility benefit as a fixed benefit per year.

10.1. PLEXOS Simulation Phases

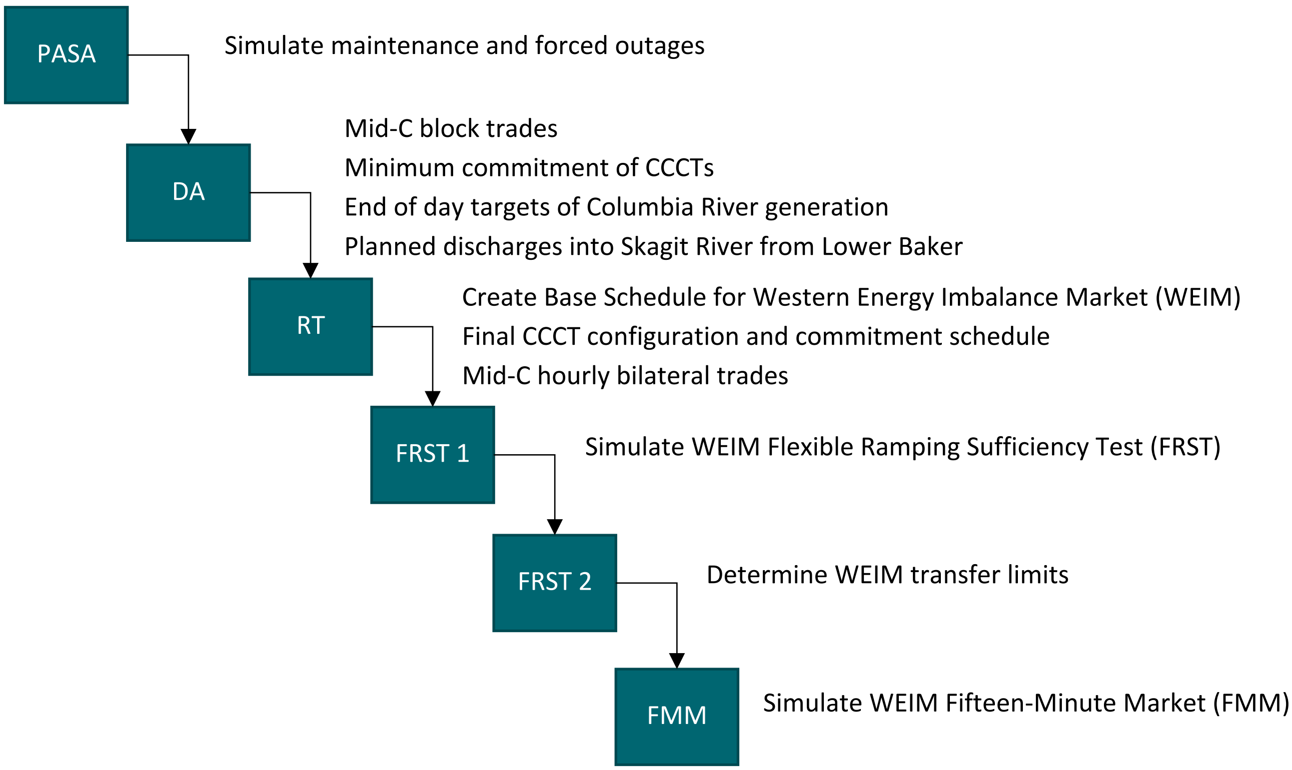
We used a multi-stage simulation approach in PLEXOS. Each stage runs separately but in sequence, so the model appropriately reflects critical decisions from earlier cycles in later decision cycles.

1. First, a model cycle in PLEXOS called Projected Assessment of System Adequacy (PASA) incorporates scheduled maintenance and random outages. It simulates the availability of the generation units with the given forced outage rates and scheduled maintenance information.
2. Then, the day-ahead stage determines a minimum plant commitment schedule for PSE's combined-cycle combustion turbine (CCCT) units, end-of-day targets for our Columbia River hydroelectric resources, planned discharges into the Skagit River from Lower Baker (Lake Shannon), and block trades for peak and off-peak hours at the Mid-C market.
3. Next, an hourly bilateral model performs finer-granularity trades at the Mid-C market and establishes the final CCCT schedule of run hours and combustion turbine (CT) commitment choices. This stage simulates a Base Schedule submitted to the California Independent System Operator's (CAISO's) Western Energy Imbalance Market (WEIM). As such, peaking units needed to balance hourly must run for the entire binding trade hour, while peaking units not committed are free to be committed by the WEIM. Additionally, as part of the Base Schedule submission, this model cycle selects operating reserves that CAISO cannot dispatch into (Spin and Non-Spin) and Regulation Up and Regulation Down, which CAISO terms Available Balancing Capacity (ABC) and can use sparingly.
4. Following the model, which simulates the creation of a Base Schedule, two 15-minute resolution models are used to perform the Flexible Ramping Sufficiency Tests (FRSTs) that CAISO uses to determine if WEIM participants have sufficient flexibility. The first model (Part 1) performs the test by simulating procurement of

the two Flexible Ramping Products (FRPs), FRP Up and FRP Down, from our system in isolation. If PLEXOS cannot procure enough FRP in one direction and/or the other, access to the WEIM market is limited to that of the previous Fifteen Minute Market (FMM) schedule in the direction(s) of test failure. The second model (Part 2) simulates WEIM interactions in the absence of any transfer limitation to determine what the transfer limits should be.

5. Finally, the model simulates FMM with all the upstream binding model decisions and FRST results.

Figure H.11: PLEXOS Simulation Phases



10.2. PLEXOS Model Inputs

We calibrated the inputs to the PLEXOS model to be as close to AURORA's input as possible for model framework consistency.

10.2.1. Contingency Reserve

Bal-002-WECC-1 requires balancing authorities to carry reserves for every hour: three percent of online generating resources and three percent of load to meet contingency obligations.

10.2.2. Balancing Reserve

Utilities must also have sufficient reserves available to maintain system reliability within the operating hour; this includes frequency support, managing load and variable resource forecast error, and actual load and generation deviations. Balancing reserves do not provide the same short-term, forced-outage reliability benefit as contingency reserves triggered by specific criteria. Balancing reserves are resources that can ramp up and down quickly as loads and resources fluctuate within a given operating hour.

E3 assessed PSE's balancing reserve requirements based on CAISO's flexible ramping product calculations. The results depend heavily on the mean average percent error (MAPE) of the hour-ahead forecasts vs. real-time values for load, wind, and solar generation.

➔ Further discussion of reserves is in Chapter Seven: Resource Adequacy Analysis.

10.2.3. Natural Gas Prices

We used a combination of forward market prices and fundamental forecasts acquired in spring 2022 from Wood Mackenzie for natural gas prices. The natural gas price forecast is an input to the AURORA electric price modeling and portfolio model.

➔ The natural gas price inputs are in Chapter Five: Key Analytical Assumptions.

10.2.4. Electric Prices

We developed the electric price forecast for the Mid-C day-ahead and hourly trades using AURORA and input to PLEXOS. We determined subhourly prices by creating imbalance supply and demand stacks from the AURORA price forecast model's solutions for Pacific Northwest resources. This methodology reflects the limited market depth subhourly and prevents PLEXOS from overestimating opportunities in imports or exports.

10.2.5. Demand Forecast

We added PSE's demand forecast to PLEXOS using the monthly energy need (MWh) and peak need (MW). We layered on historical forecast errors from CAISO's forecasting of PSE's load in 2021 and 2022 to develop day-ahead, hour-ahead, and 15-minute forecasts.

➔ A description of our demand forecast is in Chapter Six: Demand Forecast.

10.3. Flexibility Benefit

To estimate the flexibility benefit of incremental resources, PLEXOS first runs the base case, which contains only PSE's current resource portfolio, and the firm capacity necessary for the model to be resource sufficient hourly. Then, we rerun PLEXOS with one new generic resource, adjusting the firm capacity down based on the new generic resource's peak capacity contribution. We then compare the subhourly production cost result of the case with the base portfolio to the production cost of the case with the additional resource.

We ensure sufficient hourly capacity and energy by providing firm capacity up to the peak need identified in the resource adequacy study. However, we must do more work to ensure that subhourly flexibility benefits do not double-count benefits by inadvertently including traces of capacity or energy value.

Current processes in AURORA step down to hourly resolution. In the current PLEXOS framework, to perform the flexibility analysis, this reflects the hourly bilateral model described. This model simulates creating and submitting a Base Schedule to the WEIM, where charges and credits are assessed based on movements away from the Base Schedule.

In the WEIM, the load buys imbalance energy when demand is above the Base Schedule hourly load forecast and sells imbalance energy when demand is below the Base Schedule hourly load forecast. This transaction occurs because of the resolved load forecast error that refines and improves with each decision cycle. Energy generators in the WEIM sell imbalance energy when their dispatch schedule exceeds the Base Schedule energy forecast and buy imbalance energy when their dispatch schedule is below the Base Schedule energy forecast. Generators may do this by economically optimizing interactions in the WEIM and taking advantage of opportunities to the changing load forecast and resource outages.

In order to attach subhourly values to hourly decision models in AURORA, we must first determine the net direct generation cost difference as the PLEXOS model moves from its hourly bilateral cycle to the WEIM FMM cycle. For example, if the model forecasts a gas generator to dispatch at 100 MW for some operating hour (100 MWh of energy) of an hourly cycle and then schedules it to generate 50 MWh total in the FMM cycle, there is a reduction in direct generation expenses associated with producing 50 MWh less energy. Each cycle's total direct generation cost is the sum of start-up costs, fuel costs of energy dispatch, variable operations and maintenance costs, and direct emissions costs.

The model then calculates the net cost of the WEIM energy products for scheduled movements associated with the load and generators. Finally, it assesses congestion rent to reflect the revenue we receive from the price separation between PSE's system and the WEIM. When dynamic transfers are binding along the EIM Transfer System Resource (ETSR) ties between PSE and neighboring WEIM participants, price separation is likely to occur, resulting in congestion revenue associated with the transfer. Current WEIM rules establish that any ETSR not directly connected to the CAISO full market footprint has revenues split equally among the interconnecting systems. As such, the model calculates one-half of the congestion revenue returns to PSE for this flexibility benefit calculation.

The flexibility benefit is the difference between the pivot case's and the base case's subhourly costs. This value as the cost difference in a year, divided by the nameplate of the pivot resource, is used to determine the flexibility benefit in $/kW-year.

The flexibility benefit calculation process is summarized as follows:

1. Run the base case, all models from day-ahead to FMM.
2. Run the pivot case, all models from day-ahead to FMM.

3. Calculate the subhourly cost of the base case and pivot cases:

    a. Subhourly cost =
       Net direct generation cost difference
       + net cost of imbalance energy market products for PSE BAA load
       + net cost of imbalance energy generation products by PSE merchant
       + congestion revenue

4. Calculate the difference between the subhourly costs between the pivot case and base case.

5. Divide by nameplate rating to determine the nominal flexibility benefit in $/kW-year.

11. Avoided Costs

Consistent with WAC 480-100-620(13),[7] the estimated avoided costs in this section provide only general information about the costs of new power supplies, and we only used them for planning purposes. This section includes estimated capacity costs consistent with the resource plan forecast, transmission and distribution deferred costs, greenhouse gas emission costs, and the cost of energy.

11.1. Capacity

Avoided capacity costs are directly related to avoiding the acquisition of new capacity resources. The timing and cost of avoided capacity resources are tied directly to the resource plan. This value represents the average cost of capacity additions (or average incremental costs), not marginal costs.

➔ The indicative avoided capacity resource costs are in Appendix I: Electric Analysis Inputs and Results.

The costs are net capacity costs — we deducted the energy or other resource values using the Mid Scenario results. For example, frame peakers can dispatch into the market when the cost of running the plant is less than market, which creates a margin that flows back to reduce customers' rates.

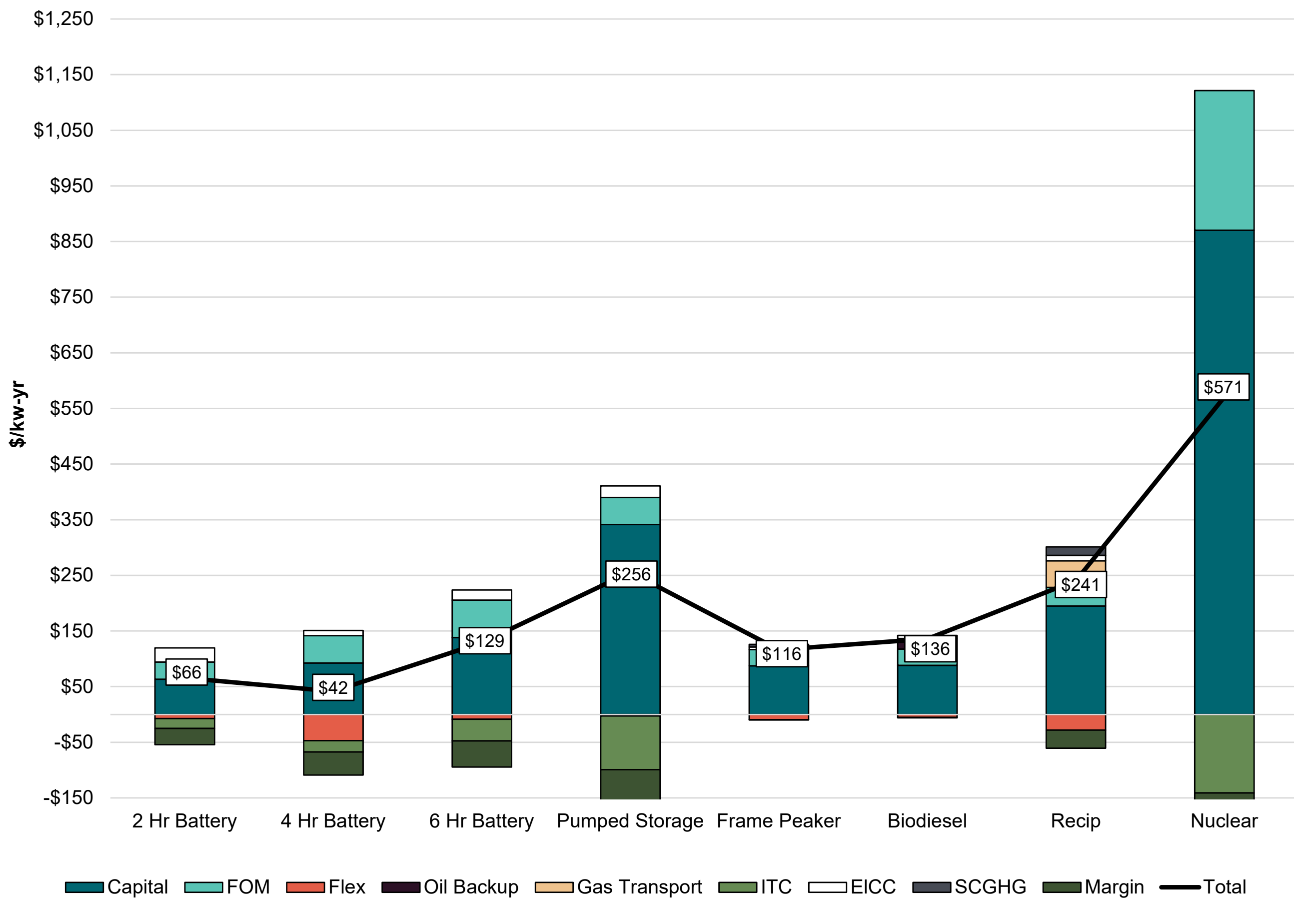
In addition to the avoided capacity cost expressed in $/kW-yr, the capacity credit of different resources needs to be specified. After specifying the annual avoided capacity resource costs by year, the avoided capacity costs include indicative adjustments to peak capacity value from this report's effective load carrying capability (ELCC) analysis.

The ELCC for a firm dispatchable resource would be 100 percent, but different intermittent resources have different peak capacity contributions. The capacity contributions used here are consistent with those described in Chapter Seven: Resource Adequacy. These results reflect the first tranche of ELCC, the first 1000 MW added to the system.

[7] WAC 480-100-620

As we add more resources to the system, the resources provide less peak capacity benefit. Figure H.12 shows the levelized cost of capacity (LCOC) compared across capacity resources.

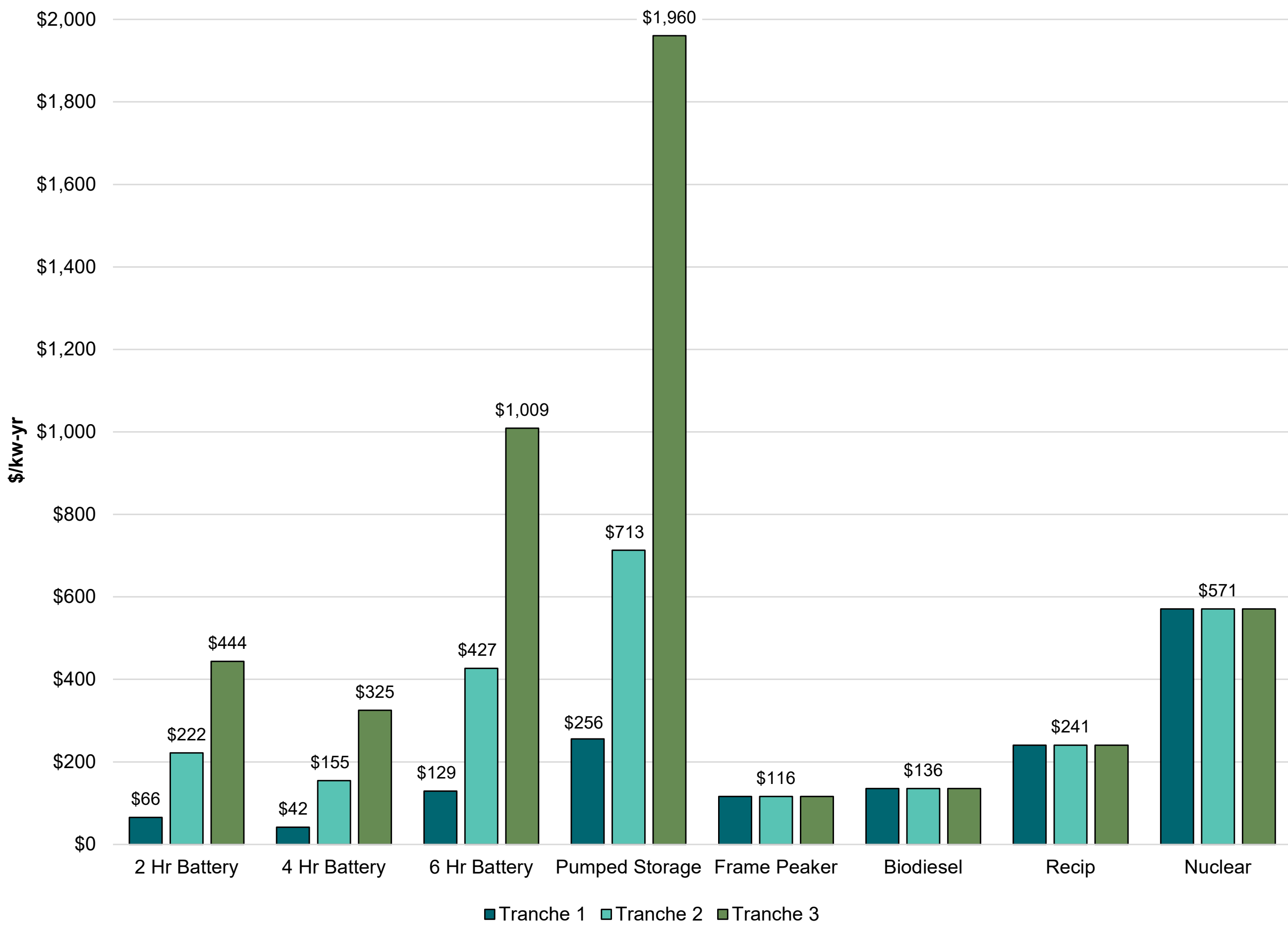
Figure H.12: Net Cost of Capacity in the Reference Portfolio



11.1.1. Saturation Curves

As we add more storage to the system with limited duration, it has less of an impact on meeting peak demand. Initially, storage can clip peaks with the shorter duration. As we add more storage to the system, the peak will flatten and require longer-duration resources to meet the peak. Figure H.13 illustrates the levelized cost impact of the tranches as described in Chapter Seven: Resource Adequacy Analysis. For example, the cost of peak capacity for a Lithium-ion 2-hour battery in Tranche 1 is $66/kW-year, and Tranche 3 is $444/kW-year.

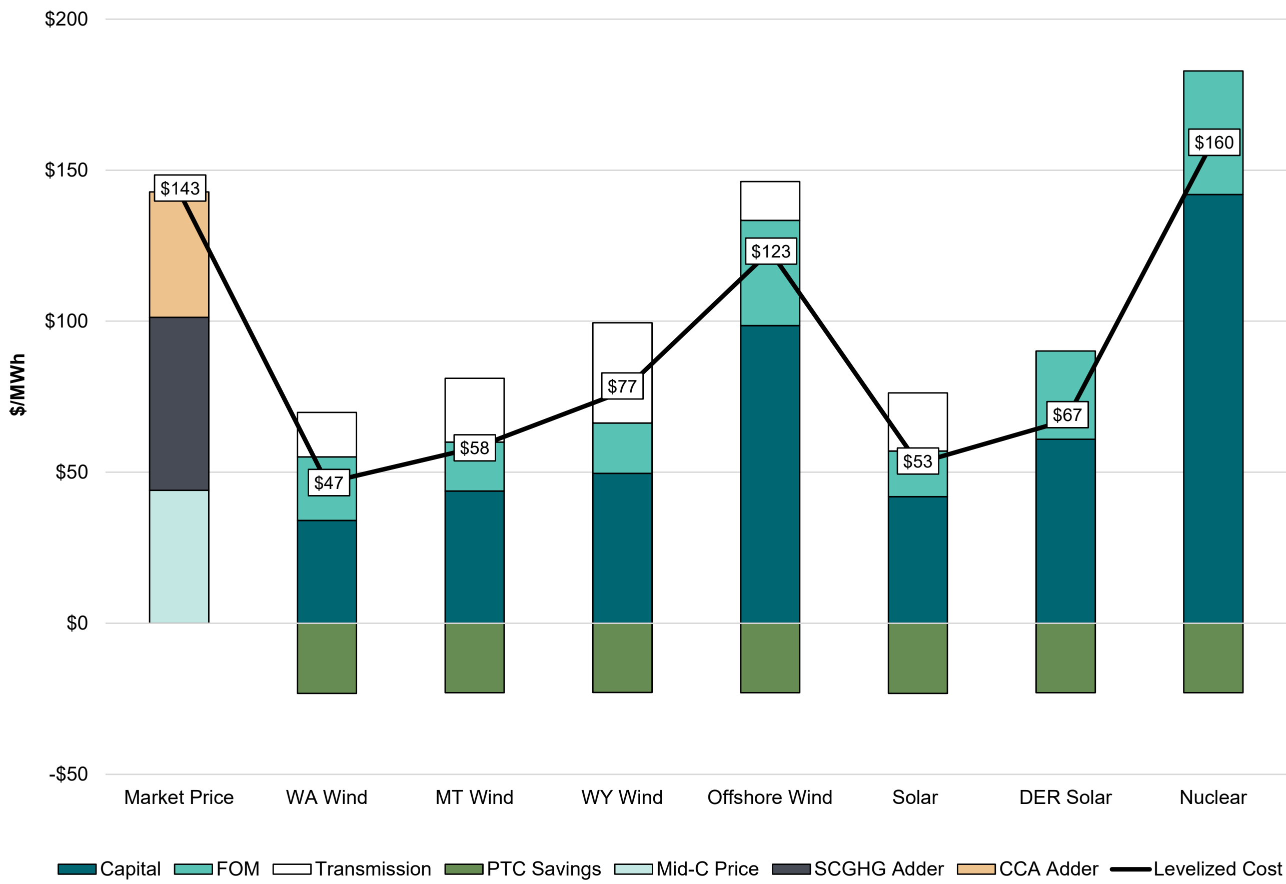
Figure H.13: Impact of Saturation Curves



11.2. Levelized Cost of Energy

We evaluated the levelized costs of energy from renewable resources based on assumptions in the reference portfolio. Renewable resource costs benefit from increased tax credits as a result of the Inflation Reduction Act. We can see the benefits in the cost component chart, Figure H.14, below the x-axis. The total energy costs do not include the peak capacity contribution to the portfolio. For example, Washington wind is the lowest cost in terms of energy because of reduced transmission costs compared to Montana and Wyoming wind. However, Montana and Wyoming wind have significantly higher peak capacity values than Pacific Northwest wind. Eastern Washington utility-scale solar is competitive in terms of energy but provides minimal peak capacity benefit. Figure H.14 illustrates the levelized costs of renewable resources to meet CETA.

Figure H.14: Levelized Cost of Energy



11.2.1. Conservation

We use bundles as the supply curve to determine the cost-effective demand-side management measures to reduce load and peak capacity. The following charts provide the cumulative cost impact as one moves up the supply curve. Figure H.15 shows an energy perspective, and Figure H.16 a capacity perspective.

Figure H.15: Conservation Cumulative Cost of Energy by Bundle

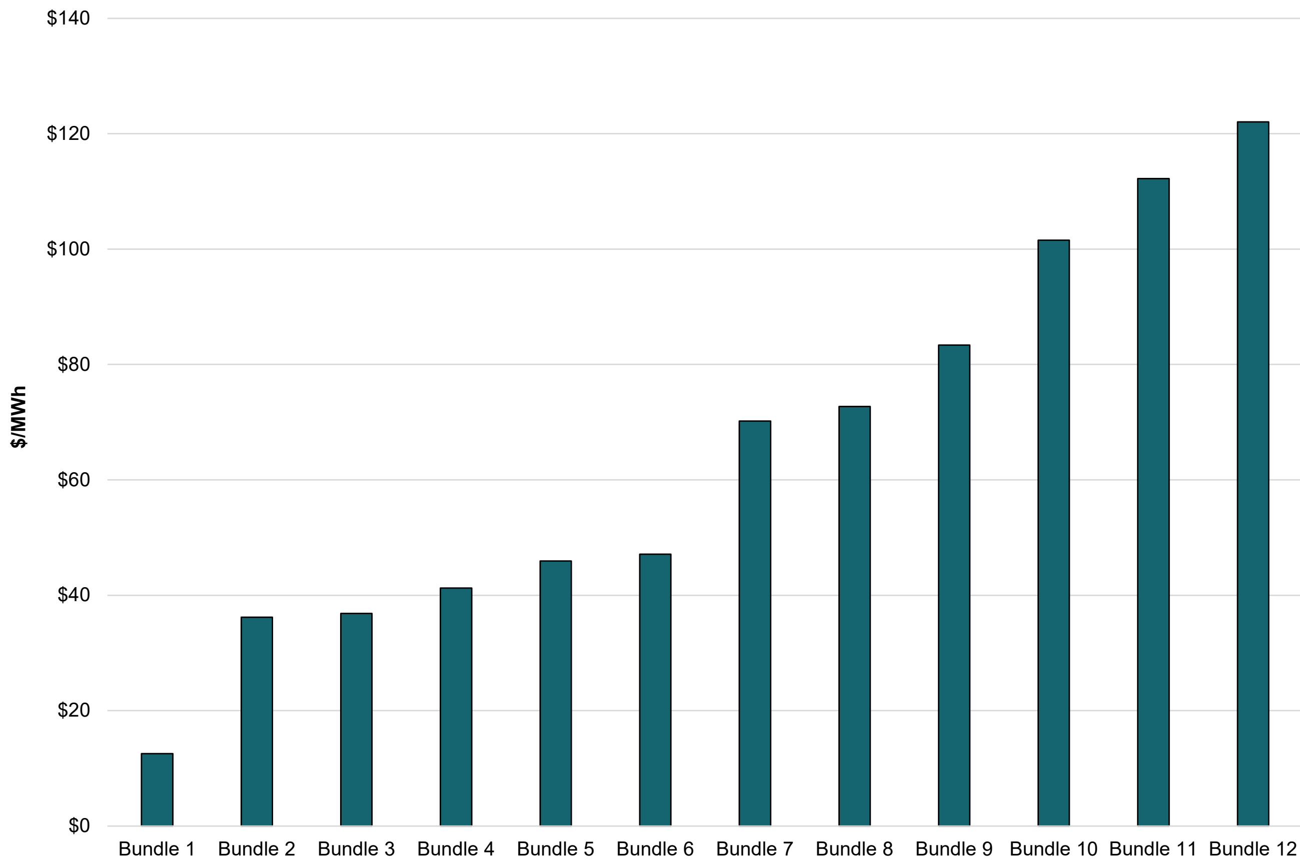
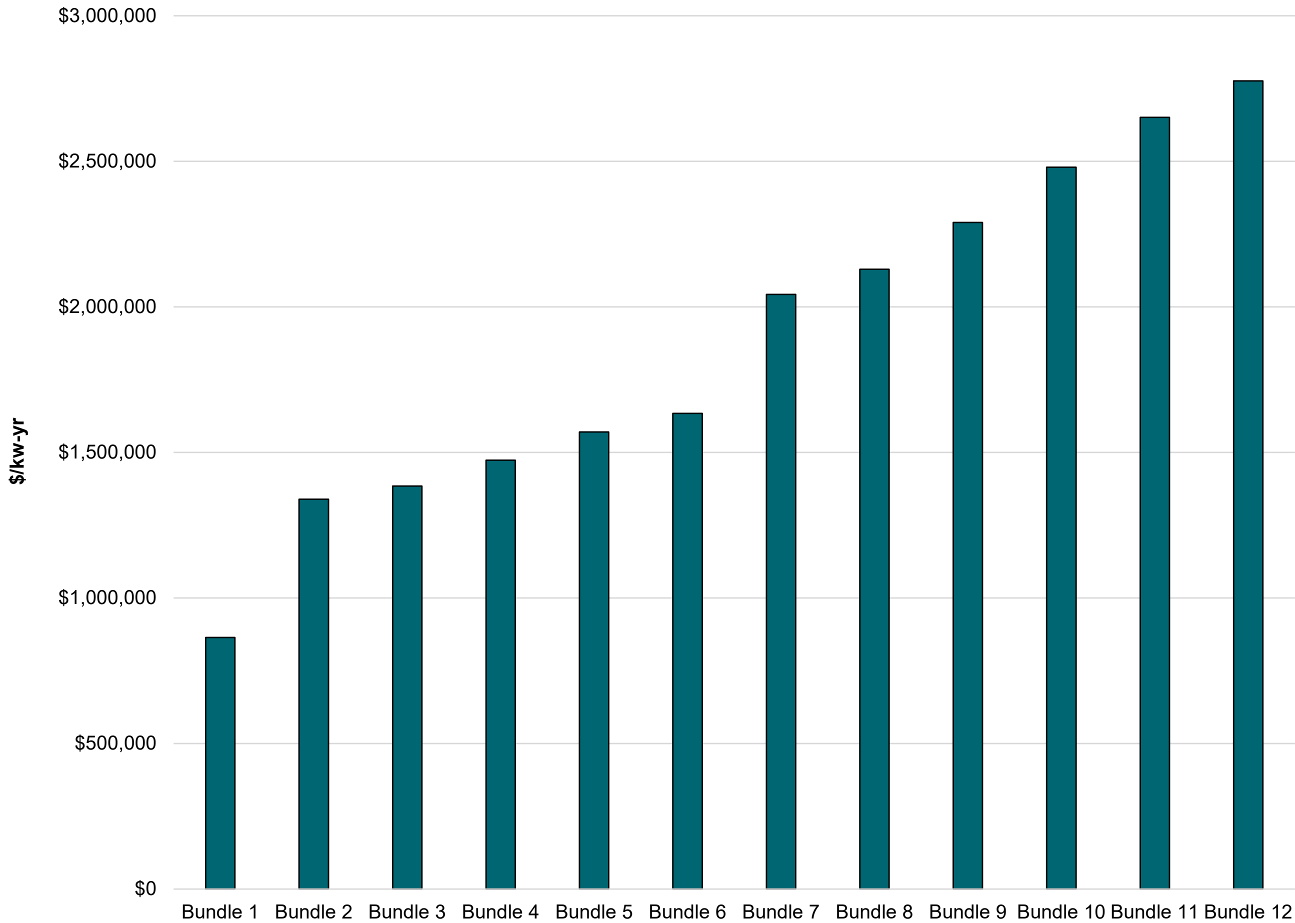


Figure H.16: Conservation Cumulative Cost of Capacity by Bundle



11.3. Deferred Transmission and Distribution Cost

The estimated avoided T&D cost is $74.70/kW-year. See the Transmission and Distribution Cost in the Financial Assumptions section of this appendix.

11.4. Avoided Costs of Greenhouse Gas Emission

This 2023 Electric Report includes modeling the SCGHG and an allowance price for the Climate Commitment Act. The emission rate for unspecified market purchases, as outlined in RCW 19.405.070, is 0.437 metric tons of CO2/MWh. Therefore, the carbon price for unspecified market purchases is the combined total of the SCGHG and the CCA GHG emission costs. See Table H.5.

Table H.5: Avoided Carbon Costs Unspecified Market Purchases $/MWh

Year	SCGHG ($/MWh)	CCA ($/MWh)	Total ($/MWh)
2024	35.43	25.31	60.74
2025	36.50	27.75	64.25
2026	37.04	28.16	65.20
2027	37.58	26.16	63.74
2028	38.11	26.73	64.84
2029	38.65	28.90	67.55
2030	39.19	27.12	66.30
2031	39.72	30.39	70.12
2032	40.26	34.06	74.32
2033	40.80	38.18	78.98
2034	41.33	42.79	84.12
2035	41.87	47.96	89.83
2036	42.41	50.45	92.85
2037	43.48	53.06	96.54
2038	44.02	55.81	99.83
2039	44.55	58.71	103.26
2040	45.09	61.75	106.84

Year	SCGHG ($/MWh)	CCA ($/MWh)	Total ($/MWh)
2041	45.63	64.95	110.58
2042	46.17	68.32	114.49
2043	46.70	71.86	118.57
2044	47.24	75.59	122.83
2045	47.78	79.51	127.29

11.5. Avoided Cost of Capacity

In Chapter Three, we documented our preferred portfolio for the 2023 Electric Report and explained why we added different resources. The first resource we added to the portfolio for capacity needs is the biodiesel peaker in 2024 at $136/kW-year. Even though we added other resources to the portfolio in the early years, we added them for different reasons. For example, distributed energy resources (DERs) such as batteries make lower peak capacity contributions and have higher costs. However, DERs play an essential role in balancing utility-scale renewable investments and transmission constraints while meeting local distribution system needs and improving customer benefits, which is why we used the frame peaker as the avoided cost of capacity.

Table H.6: shows the avoided capacity costs we estimated in this 2023 Electric Report. Under WAC 480-106-040(b)(ii),[8] the 2023 report's first capacity addition in 2024 is a biodiesel peaker, the basis for the peak capacity avoided cost. The results reflect the cost of the biodiesel peaker net of the ELCC for the biodiesel peaker, wind, and solar.

Table H.6: 2023 Avoided Capacity Costs (Nominal $/kW-yr)

Year	Capacity Resource Addition	(a) Levelized Net $/kW-year Delivered to PSE	(c)=(a) Firm Resource ($)	(d)=(a)*0.13 Wind Resource ELCC=13% ($)	(e)=(a)*0.04 Solar Resource ELCC=4% ($)
2024	Baseload Resource	135.69	135.69	17.64	5.43
2025	Baseload Resource	135.69	135.69	17.64	5.43
2026	Baseload Resource	135.69	135.69	17.64	5.43
2027	Baseload Resource	135.69	135.69	17.64	5.43
2028	Baseload Resource	135.69	135.69	17.64	5.43
2029	Baseload Resource	135.69	135.69	17.64	5.43

[8] WAC 480-106-040

Year	Capacity Resource Addition	(a) Levelized Net $/kW-year Delivered to PSE	(c)=(a) Firm Resource ($)	(d)=(a)*0.13 Wind Resource ELCC=13% ($)	(e)=(a)*0.04 Solar Resource ELCC=4% ($)
2030	Baseload Resource	135.69	135.69	17.64	5.43
2031	Baseload Resource	135.69	135.69	17.64	5.43
2032	Baseload Resource	135.69	135.69	17.64	5.43
2033	Baseload Resource	135.69	135.69	17.64	5.43
2034	Baseload Resource	135.69	135.69	17.64	5.43
2035	Baseload Resource	135.69	135.69	17.64	5.43
2036	Baseload Resource	135.69	135.69	17.64	5.43
2037	Baseload Resource	135.69	135.69	17.64	5.43
2038	Baseload Resource	135.69	135.69	17.64	5.43
2039	Baseload Resource	135.69	135.69	17.64	5.43
2040	Baseload Resource	135.69	135.69	17.64	5.43
2041	Baseload Resource	135.69	135.69	17.64	5.43
2042	Baseload Resource	135.69	135.69	17.64	5.43
2043	Baseload Resource	135.69	135.69	17.64	5.43
2044	Baseload Resource	135.69	135.69	17.64	5.43
2045	Baseload Resource	135.69	135.69	17.64	5.43
2046	Baseload Resource	135.69	135.69	17.64	5.43
2047	Baseload Resource	135.69	135.69	17.64	5.43

11.6. Schedule of Estimated Avoided Costs for PURPA

This schedule of estimated avoided costs, as prescribed in WAC 480-106-040,[8] identifies the estimated avoided costs for qualifying facilities and did not provide a guaranteed contract price for electricity. The schedule only identifies general information to potential respondents about the avoided costs. The schedule of estimated avoided costs includes table H.7.

Table H.7: Schedule of Estimated Avoided Costs

Year	Jan ($/MWh)	Feb ($/MWh)	Mar ($/MWh)	Apr ($/MWh)	May ($/MWh)	Jun ($/MWh)	Jul ($/MWh)	Aug ($/MWh)	Sept ($/MWh)	Oct ($/MWh)	Nov ($/MWh)	Dec ($/MWh)	Avg. ($/MWh)
2024	39.63	34.62	28.06	25.48	18.80	25.90	41.99	39.52	43.83	37.21	37.83	42.11	34.60
2025	36.53	35.25	28.43	25.91	18.10	25.72	43.40	39.52	45.69	39.52	38.58	44.07	35.07
2026	40.56	37.51	28.65	26.60	19.30	27.72	48.36	43.13	48.76	42.21	40.09	47.36	37.54
2027	44.76	43.26	33.36	29.87	20.67	32.23	54.24	48.89	54.25	46.43	45.05	50.92	42.00
2028	48.81	43.09	33.96	30.33	22.08	32.79	55.96	51.51	54.65	47.06	46.28	54.19	43.42
2029	47.16	41.67	31.04	29.90	21.21	30.97	56.35	53.98	59.35	49.82	47.93	53.70	43.62
2030	47.25	41.25	28.86	27.96	21.28	30.19	57.33	53.89	58.43	49.54	47.17	53.66	43.11
2031	43.73	41.48	28.51	30.42	18.73	30.98	58.78	54.89	59.99	50.06	47.64	54.63	43.35
2032	45.70	40.25	27.30	27.92	17.50	32.21	59.80	56.79	63.91	51.87	48.94	56.06	44.05
2033	45.97	42.63	28.01	27.41	17.08	33.43	66.18	62.35	62.92	54.36	50.75	61.17	46.08
2034	44.72	39.55	29.17	29.93	18.57	34.77	69.13	60.31	65.16	57.12	52.61	60.22	46.84
2035	48.13	42.67	29.00	29.97	18.76	32.11	73.47	67.31	74.18	59.98	54.95	63.40	49.57
2036	51.27	40.68	27.93	28.88	17.96	33.34	78.64	69.53	74.86	58.73	53.78	64.03	50.05
2037	47.53	43.33	31.94	29.07	15.61	34.48	80.66	72.61	79.31	59.44	55.46	66.95	51.45
2038	48.74	39.85	27.70	28.54	16.53	34.02	84.20	70.73	80.97	63.14	56.52	70.80	51.93
2039	51.29	43.69	28.06	28.31	16.45	39.28	86.83	74.81	80.62	62.83	59.70	71.77	53.74
2040	49.87	40.71	29.20	28.94	18.16	40.70	89.73	75.98	82.77	66.41	56.38	73.33	54.45
2041	58.79	45.67	28.21	29.94	14.90	35.20	92.56	83.56	89.62	66.93	63.05	75.47	57.11
2042	59.15	44.92	26.89	29.51	14.59	38.35	101.79	92.74	91.72	66.90	61.39	81.39	59.27
2043	59.81	44.28	30.51	28.65	15.73	42.72	107.66	89.90	96.07	67.15	64.72	84.67	61.16