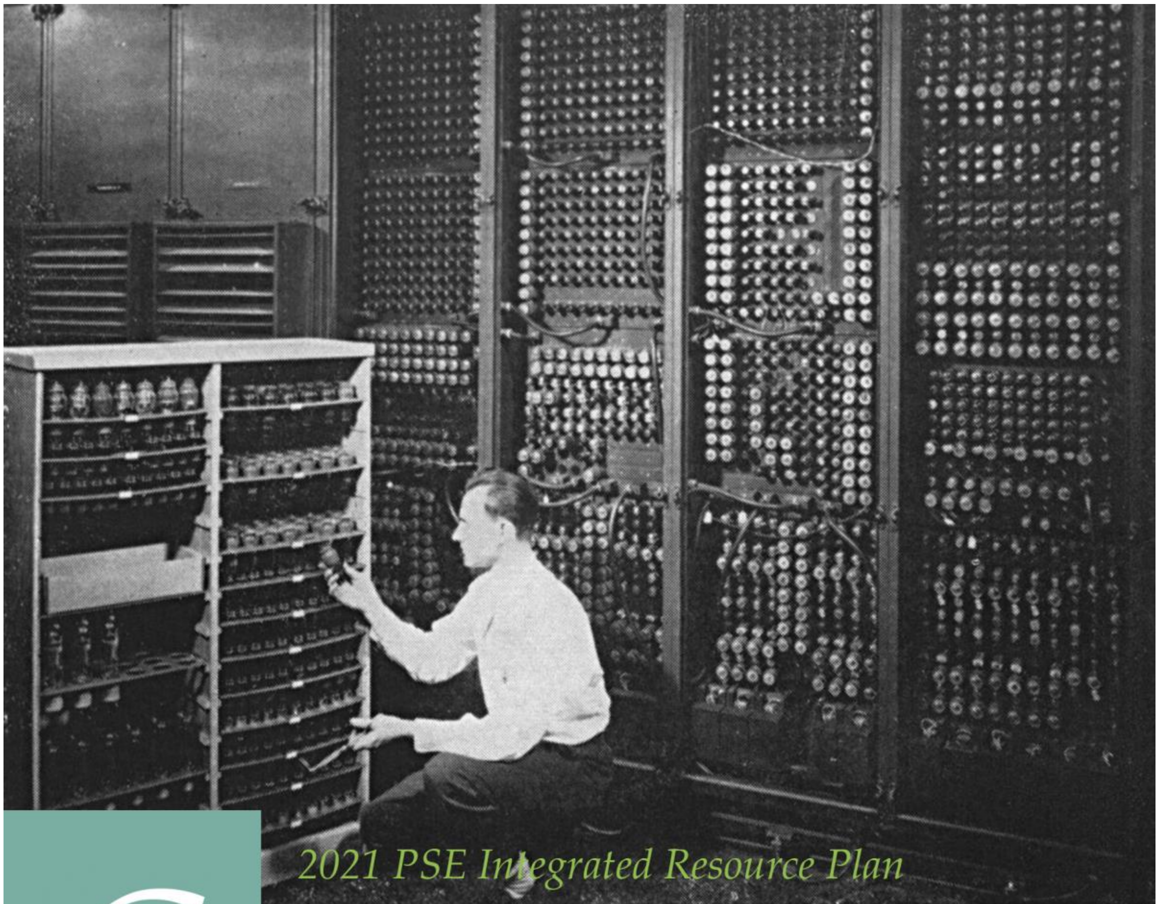


G Electric Analysis Models

This appendix describes the analytical models used in the electric analysis for the 2021 IRP.

Contents

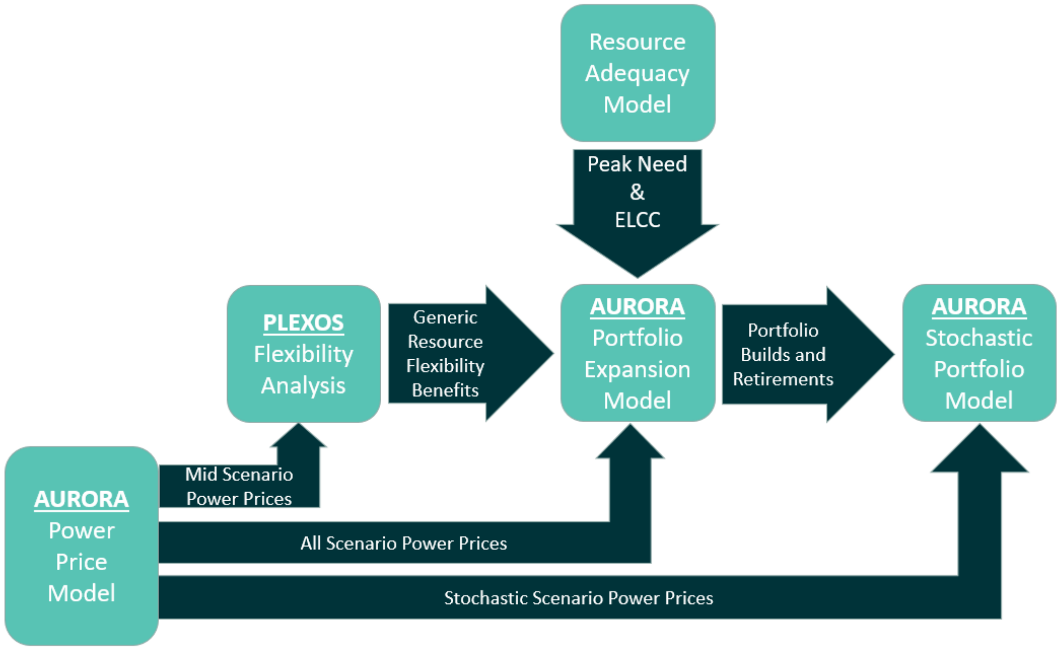
1. ELECTRIC MODELING PROCESS

PSE uses three models for electric integrated resource planning: AURORA, PLEXOS and the Resource Adequacy Model (RAM). AURORA is used 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 these portfolios to evaluate PSE's long-term revenue requirements for the incremental portfolio and the risk of each portfolio, and 3) in the stochastic analysis, the model is used to create simulations and distributions for various variables. PLEXOS estimates the cost savings due to sub-hour operation for new generic resources. PSE's probabilistic Resource Adequacy Model enables PSE to assess the following; 1) to quantify physical supply risks as PSE's portfolio of loads and resources evolves over time, 2) to establish peak load planning standards, which in turn leads to the determination of PSE's capacity planning margin, and 3) to quantify the peak capacity contribution of a renewable and energy-limited resource (its effective load carrying capacity, or ELCC). The peak planning margin and ELCCs are inputs into PSE's portfolio expansion model. A full description of RAM is in Chapter 7.

Figure G-1 demonstrates how the models are connected. The following steps are used to get to the least-cost portfolio for each of the scenarios and sensitivities.

1. Create Mid-C power prices in AURORA for each of the five electric price scenarios.
2. Using the Mid Scenario Mid-C prices from AURORA, run the flexibility analysis in PLEXOS to find the flexibility benefit for each of the generic supply-side resources.
3. Run RAM 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 for new portfolio builds and retirements for each of the 37 different scenario and sensitivity portfolios.
5. Develop stochastic variables around power prices, gas prices, hydro generation, wind generation, PSE loads and thermal plant forced outages.

Figure G-1: Electric Analysis Methodology



AURORA Electric Price Model

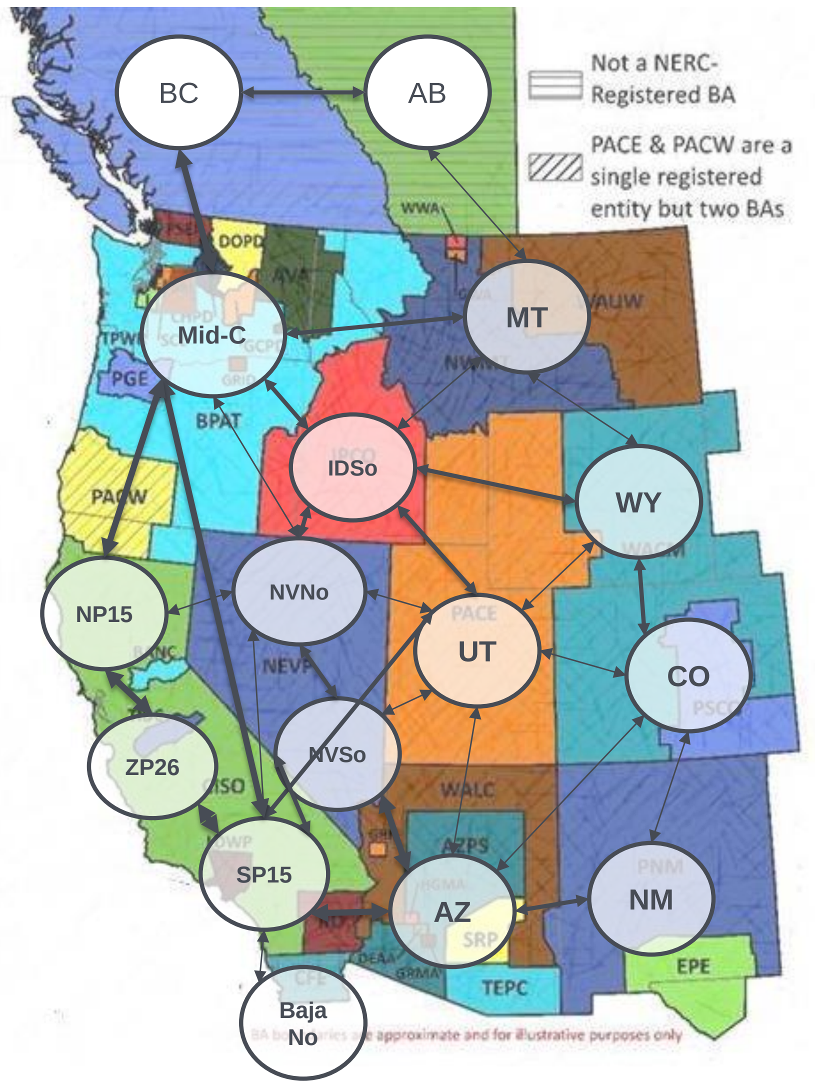
A power price forecast is developed for each of the scenarios modeled in an IRP. In this context, “power price” does not mean the rate charged to customers, it means the price to PSE of purchasing (or selling) 1 megawatt (MW) of power on the wholesale market given the economic conditions that prevail in that scenario. This is an important input to the analysis, since market purchases make up a substantial portion of PSE’s resource portfolio.

Creating wholesale power price assumptions requires performing two WECC-wide AURORA model runs for each scenario. (AURORA is the hourly chronological price forecasting model based on market fundamentals used widely throughout the IRP process.)

- The first AURORA run identifies the capacity expansion needed to meet regional loads. AURORA looks at loads and peak demand plus a planning margin, and then identifies the most economic resource(s) to add to make sure that all of the regions modeled are in balance.

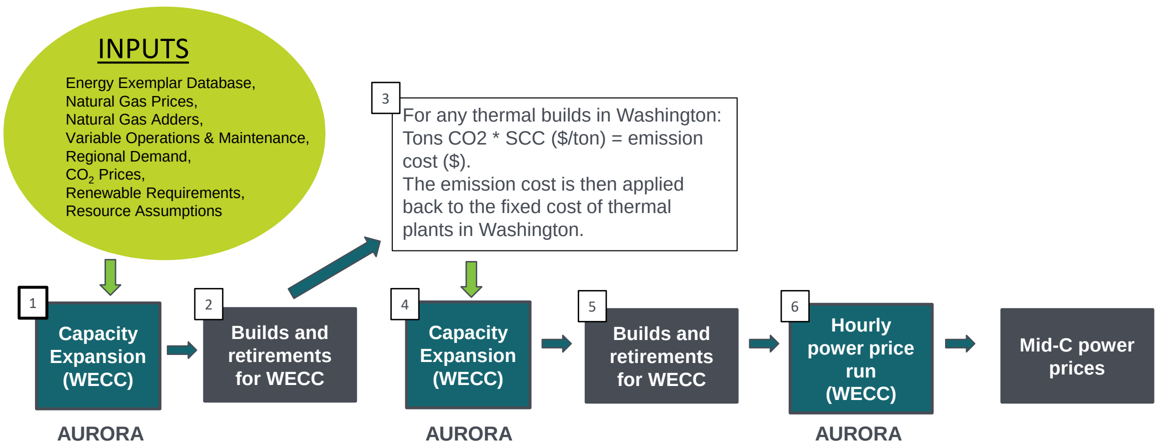
- The second AURORA run produces hourly power prices. A full simulation across the entire WECC region produces power prices for all of the 16 zones shown in Figure G-2. The lines and arrows in the diagram indicate transmission links between zones. The heavier lines represent greater capacity to flow power from one zone to another.

Figure G-2: AURORA System Diagram



The Pacific Northwest Zone, labeled Mid-C in the diagram above, is modeled as the Mid-Columbia (Mid-C) wholesale market price. The Mid-C market includes Washington, Oregon, Northern Idaho and Western Montana. Figure G-3 illustrates PSE's process for creating wholesale market power prices.

Figure G-3: PSE IRP Modeling Process for AURORA Wholesale Power Prices



PSE's electric price model follows a six-step process to forecast wholesale electric prices.

1. Long run capacity expansion for the Western Electricity Coordinating Council (WECC). The database includes only existing and planned resources for the next few years, but with load growth, there are not enough resources to meet needs for the next 20 years. So, PSE runs a capacity expansion to add new generic resources to make sure the WECC stays in load resource balance.
2. The long run capacity expansion produces a set of builds and retirements for the WECC.
3. PSE pulls the builds for Washington state and looks for any new natural gas plants added to Washington state. PSE then calculates the social cost of greenhouse gas (SCGHG) adder for any natural gas plants added in Washington.
4. The capacity expansion model is then re-run with the SCGHG adder.
5. The updated model then produces a set of builds and retirements for the WECC that include the SCGHG adder for Washington state.
6. This final set of builds and retirements is then run through the standard zonal model in AURORA for every hour of the 20 years for a complete dispatch.
7. This standard zonal hourly dispatch then produces an electric price forecast for each zone identified in Figure G-2 above. PSE uses the price forecast for the Mid-C zone as the wholesale market price in the portfolio model.

Electric Price Model Inputs

Electric price model inputs are summarized in Chapter 5; additional detail is provided below as appropriate.

ENERGY EXEMPLAR DATABASE. PSE used Energy Exemplar's AURORA database titled "US_CANADA_DB_2018_V1" released in January 2018. The databased included extensive updates to demand, fuels, resources, transmission links and monthly hydro availability since the last database release.

- Historical hourly demand was derived directly from WECC Transmission Expansion Planning Policy Committee Load Zones for all years through 2016. 10-year forecasts were derived from reported Planning Areas in the 2016 FERC-714.
- Transmission links were updated based on the WECC 2016 Power Supply Assessment.
- Resources were updated to reflect the 2016 EIA-860, with supplemental information from the August 2017 EIA-860M and the 2016 EIA-923 datasets.
- Historical Hydro 80 Water years were updated to reflect assumptions available from the Bonneville Power Administration (BPA, as delivered by the Northwest Power and Conservation Council). At the time of the release, the report reflected hydro output to be used for the Pacific Northwest Power Supply Adequacy Assessment for 2023.

NATURAL GAS PRICES. For natural gas prices, PSE uses a combination of forward market prices and fundamental forecasts acquired in Spring 2020 from Wood Mackenzie. The natural gas price forecast is an input into the AURORA Electric Price Modeling and AURORA Portfolio Model. The natural gas price inputs are described in Chapter 5.

NATURAL GAS ADDERS AND VARIABLE OPERATIONS & MAINTENANCE (VOM). The Energy Exemplar database uses Henry Hub gas prices as the base fuel price. So, in the database, the fuel price adders are used as the basis differential between Henry Hub and the other fuel hubs. Since PSE inputs the different hub prices, the adders are updated to be pipeline tariff rates to get the burner tip price.

Figure G-4: Fuel Adders for Sumas and Stanfield

Fuel Hub	Adder	Default Fuel Adder	Revised Fuel Adder
Sumas	NGNW-Coastal	-0.20	0.06
Sumas	NG1NW-Coastal	0.32	0.13
Sumas	NG2NW-Coastal	0.29	0.21
Sumas	NG3NW-Coastal	0.63	0.28
Stanfield	NGNW-Inland	-0.20	0.06
Stanfield	NG1NW-Inland	0.32	0.07
Stanfield	NG2NW-Inland	0.29	0.13
Stanfield	NG3NW-Inland	0.63	0.20

REGIONAL DEMAND. This IRP uses the regional demand developed by the NPCC[1] 2019 Policy Update to the 2018 Wholesale Electricity Forecast, the most recent forecast available at the time of this analysis. Updated 2020 loads and COVID-19 impacts were not available from the NPCC until February 2021. Regional demand is used only in the WECC-wide portion of the AURORA analysis that develops wholesale power prices for the scenarios.

RENEWABLE REQUIREMENTS. Renewable portfolio standards (RPS) and clean energy standards currently exist in 29 states and in the District of Columbia, including most of the states in the WECC and British Columbia. Each state and territory defines renewable energy sources differently, sets different timetables for implementation, and establishes different requirements for the percentage of load that must be supplied by renewable resources. PSE incorporated renewable portfolio and clean energy standards passed in and before the year 2020. All of these renewable requirements are detailed in Chapter 5.

CO_2 PRICES. The social cost of greenhouse gases (SCGHG) cited in the Washington Clean Energy Transformation Act (CETA) as a cost adder to thermal resources in Washington state is included in the electric price modeling. Detailed inputs are provided in Chapter 5 and the Excel file with the numbers used is included as part of Appendix H.

1 / The NPCC has developed some of the most comprehensive views of the region's energy conditions and challenges. Authorized by the Northwest Power Act, the Council works with regional partners and the public to evaluate energy resources and their costs, electricity demand and new technologies to determine a resource strategy for the region.

RESOURCE ASSUMPTIONS. As a part of the electric price modeling process, PSE uses the standard database for the WECC region provided by Energy Exemplar with the AURORA modeling software. This database includes information on the retirement dates of existing resources in the WECC system, as well as build and retirement dates for planned resources that are not currently in operation.

Long-run Optimization

AURORA also has the capability to simulate the addition of new generation resources and the economic retirement of existing units through its long-term optimization studies. This optimization process simulates what happens in a competitive marketplace and produces a set of future resources that have the most value in the marketplace. New units are chosen from a set of available supply alternatives with technology and cost characteristics that can be specified through time. New resources are built only when the combination of hourly prices and frequency of operation for a resource generate enough revenue to make construction profitable, unless reserve margin targets are selected. (That is, when investors can recover fixed and variable costs with an acceptable return on investment.) AURORA uses an iterative technique in these long-term planning studies to solve the interdependencies between prices and changes in resource schedules.

WECC Coal Plant Retirements

PSE added constraints on coal technologies to the AURORA model in order to reflect current political and regulatory trends. Specifically, no new coal builds were allowed in any state in the WECC. Planned retirements are shown in Figure G-5 below.

Figure G-5: Planned Coal Retirements across the WECC

Plant Name	State	Nameplate MW	Retirement Year
Colstrip 3	MT	740	2025
Colstrip 4	MT	740	2025
North Valmy 2	NV	268	2025
Centralia 2	WA	670	2025
Jim Bridger 1	WY	531	2028

WECC Renewable Builds

PSE added 3,123 MW of renewable resources to Energy Exemplar's US_CANADA_DB_2018_V1 database based on the data from the S&P Global Data[2] as of February 2020. Figure G-6 provides new build capacity for solar and wind resources from 2016 to 2024. The majority of the new renewable resources are located in the California region.

Figure G-6: Planned New Builds in the WECC (USA)

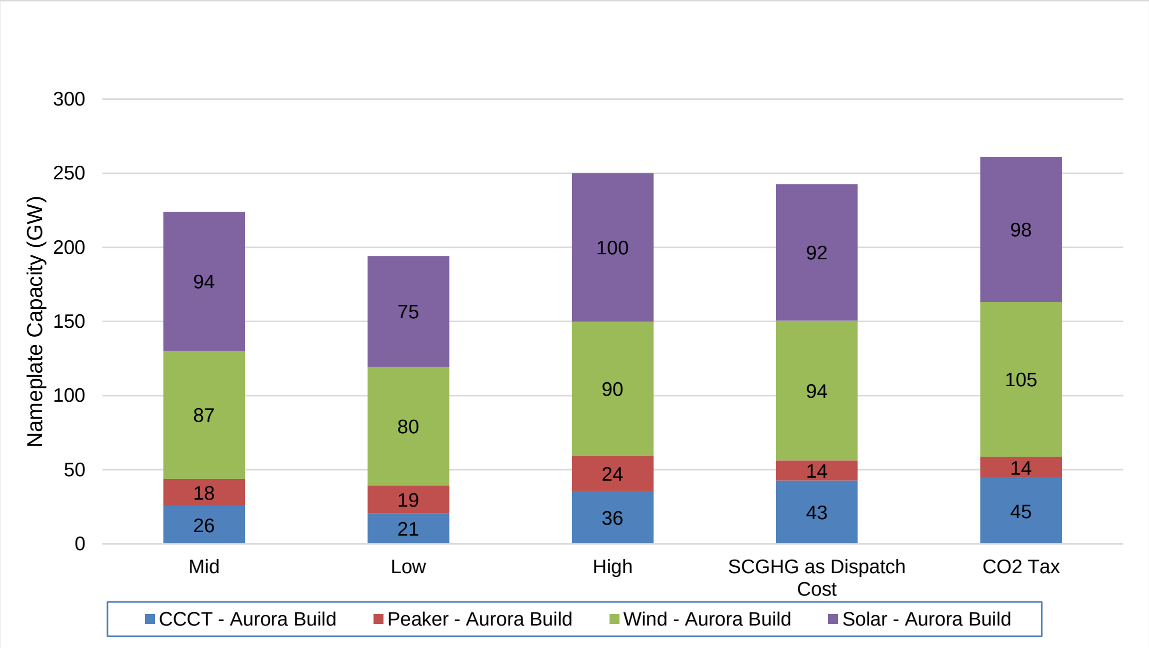
Planned Renewable Build	MW
Solar	1,607
Wind	1,516
Total Planned Build	**3,123**

2 / S&P Global formerly known as SNL, which stands for Savings and Loan, is a company that collects and disseminates corporate, financial and market data on several industries including the energy sector (www.spglobal.com).

AURORA Builds

AURORA is able to run a long-term optimization model to choose a set of available supply to meet both energy needs and peak needs. New resources are built only when the combination of hourly prices and frequency of operation for a resource generate enough revenue to make construction profitable. Figure G-7 shows AURORA builds in the five scenarios for both the U.S. and Canada WECC.

Figure G-7: WECC Aurora Builds by 2045



Power Price Forecast Results

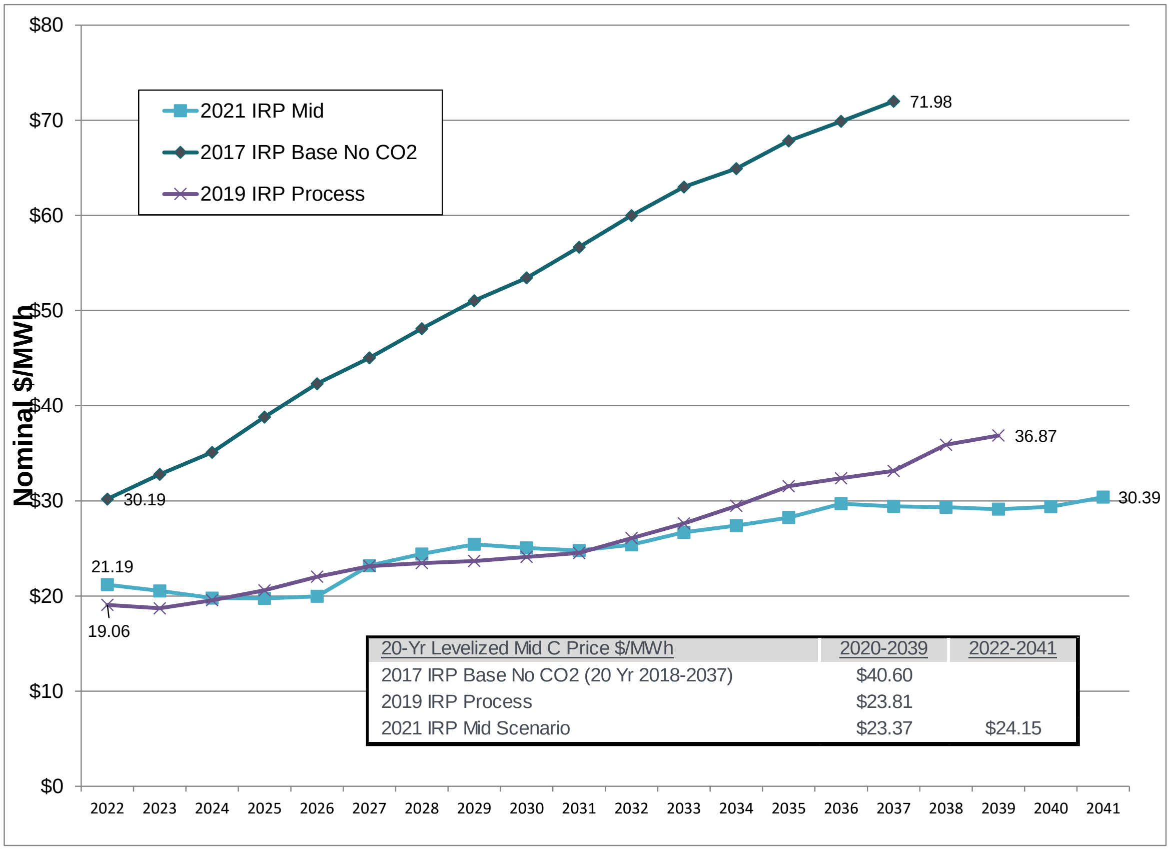
The table below increments through the updates to power prices from the 2019 IRP progress report power prices to the final power prices filed in the 2021 IRP. The 2019 IRP time frame was 2020 – 2039 and the 2021 IRP time frame is 2022 – 2041.

Figure G-8: Changes in Power Prices from 2019 IRP Progress Report to 2021 IRP

	Nominal ($/MWh)	20-yr Levelized	Incremental Difference	Cumulative Difference from 2019 IRP Progress Report
2017 IRP Base + No CO2		$40.60		
0	2019 IRP Progress Report Mid Scenario	$23.81	($16.79)	
1	Modeling updates for the Draft Power Prices • Updated Aurora from version 13.3 to version 13.4 • Updated New Builds and Retirements using SNL Data • Gas Price Update using Fall 2019 Wood Mackenzie Forecast	$24.47	$0.66	$0.66
2	Modeling updates for the Final Power Prices • Update Regional Demand using the Northwest Power and Conservation Council (NPCC) 2019 Policy Update to the 2018 Wholesale Electricity Forecast • Gas Prices from Spring 2020 Long Term View Price Update from Wood Mackenzie • Update estimated state sales forecast for Clean Energy Targets - Final Mid Scenario	$24.15	($0.32)	$0.34

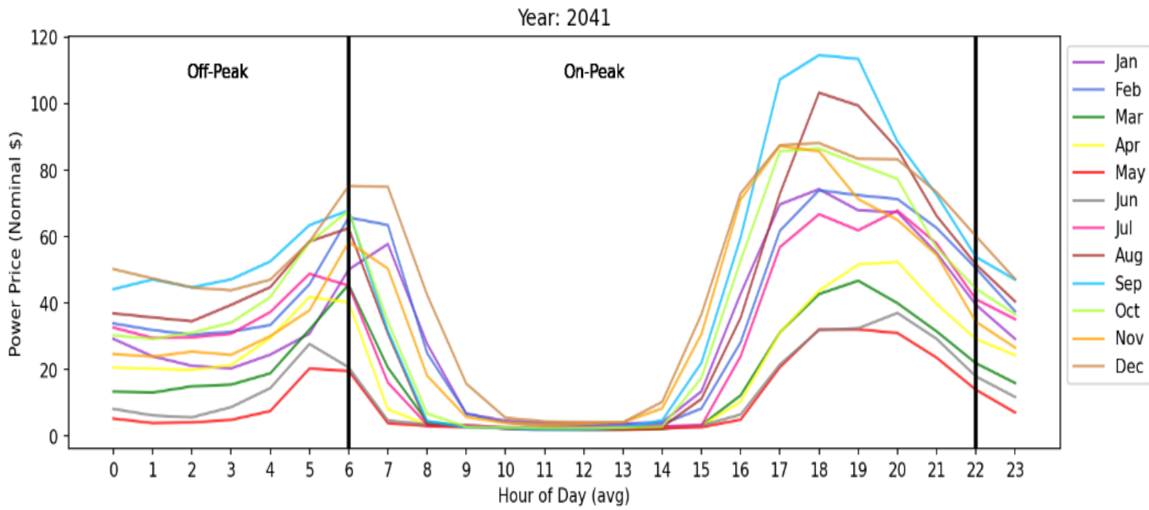
Figure G-9 below is a comparison of the annual average Mid-C power price from the 2017 IRP and 2019 IRP Progress Report to the 2021 IRP. The increase in renewable resources in the region is causing the decrease in power prices. The power prices are based on the cost of the marginal resource in each hour. Given the large amount of renewable resources, they are pushing out the dispatch curve, and the renewable resources are now the marginal unit in many hours. The dispatch cost of a renewable resource is $0, so the price for that hour is now $0. With many hours at around $0, the average cost of power is significantly lower than the 2017 IRP

Figure G-9: Comparison of Mid-C Annual Average Power Price



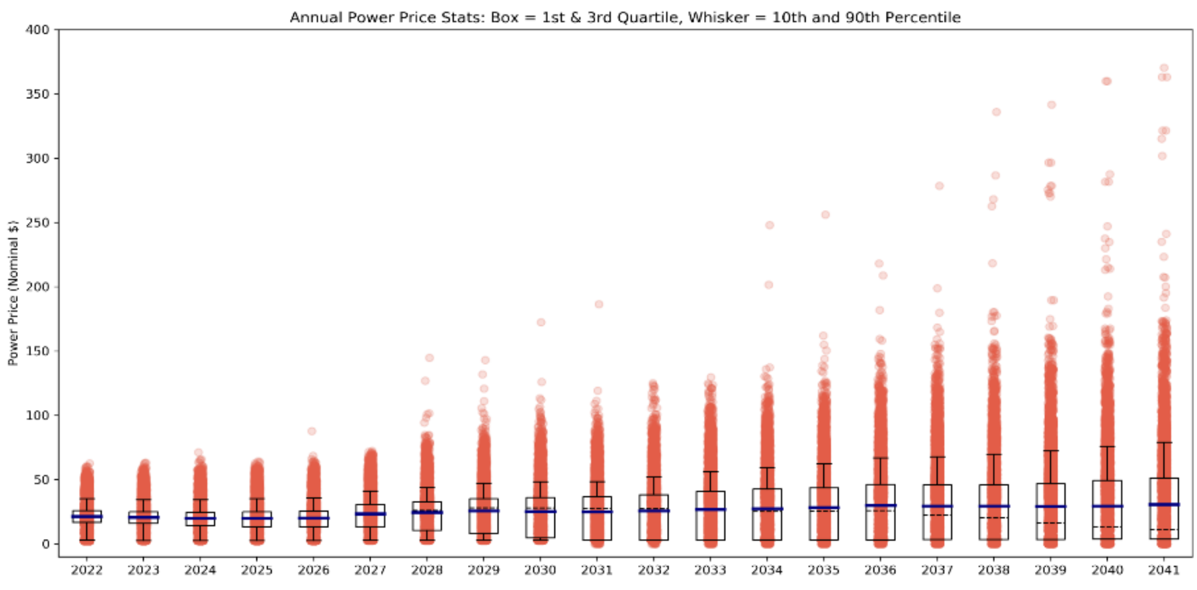
However, the increased supply of intermittent resources causes significant price volatility. As the renewable resources fall off in the evening, costly peaking resources pick up the supply, which results in larger swings in power prices from on-peak to off-peak. Figure G-10 below is the average hourly power price for each month in 2041. This growing difference in hourly prices between mid-day and morning/evening peak increases with more renewables

Figure G-10: 2041 Hourly Mid-C Price Shape by Month



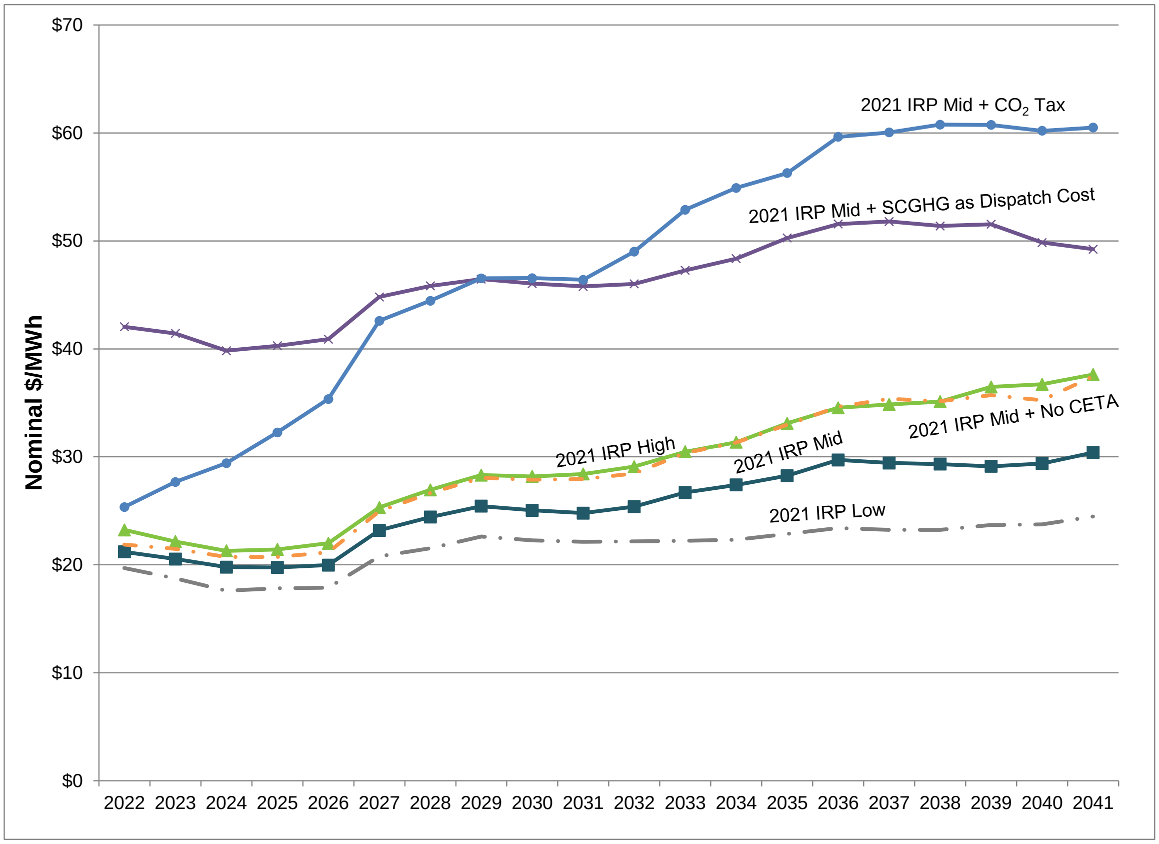
Mid-C price forecasts are highly variable even under normal hydro conditions and assuming a fully optimized wholesale market. Figure G-11 shows the hourly Mid-C Price from 2022 through 2041. In the late years, the hourly prices become more volatile and there is a growing number of high-price hours as more renewables are added to the system. A divergence of the median and mean power price is seen in the late years, indicating a lot of low power prices, but a few very expensive prices pulling up the mean.

Figure G-11: Hourly Mid-C Price from 2022 through 2041



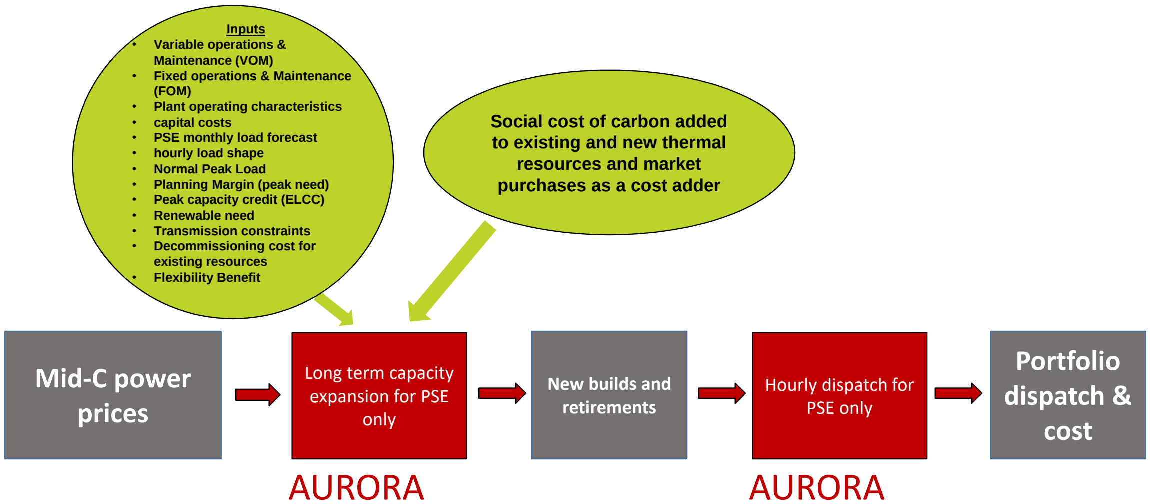
PSE created low, mid and high scenarios for the electric analysis to test how different combinations of two fundamental economic conditions – customer demand and natural gas prices – impact the least-cost mix of resources. Along with testing changes to economics impacts, PSE also ran two scenarios with different CO_2 prices. Figure G-12 below show the annual average Mid-C price forecast for the low, mid, high, and two CO_2 price scenarios.

Figure G-12: Annual Average Mid-C Power Price Forecast



AURORA Portfolio Model

Figure G-13: Aurora Portfolio Model



PSE's electric portfolio model follows a seven-step process to forecast wholesale electric prices.

1. A Long Term Capacity Expansion (LTCE) model is used to forecast the installation and retirement of resources over a long-term planning horizon not only to keep pace with energy and peak need but also to meet the renewable requirement to be CETA and RPS compliant.
2. The LTCE run produces a set of builds and retirements for PSE.
3. PSE then calculates the social cost of greenhouse gas (SCGHG) adder for any existing and new natural gas plants.
4. The capacity expansion model is re-run with the SCGHG adder.
5. The updated model then produces a set of builds and retirements for PSE that include the SCGHG as a planning adder.
6. This final set of builds and retirements is then run through the standard zonal model in AURORA for every hour of the 24-years for a complete dispatch.
7. This standard zonal hourly dispatch then produces the portfolio dispatch and cost.

Long-Term Capacity Expansion Model

A Long-Term Capacity Expansion simulation (LTCE) is used to forecast the installation and retirement of resources over a long period of time. Over the study period of an LTCE simulation, existing resources may be retired and new resources are added to the resource portfolio.

To perform the LTCE modeling process, PSE uses a program called AURORA provided by Energy Exemplar. AURORA is an algebraic solver software used to complete analyses and forecasts of the power system that has been used for decades within the utility industry. The software provides a variety of functions that allow PSE to perform analyses quickly and efficiently, while maintaining a rigorous record of the data used to perform simulations.

The LTCE model begins the resource planning process by taking into account the current fleet of resources available to PSE, the options available to fill resource needs, and the necessary planning margins required for fulfilling resource adequacy needs. The resource need is calculated dynamically as the simulation is performed using demand forecasts. The LTCE model has the discretion to optimize the additions and retirements of new resources based on resource need, economic conditions, resource lifetime and competitive procurement of new resources. The new resources that are available to the model to acquire are established prior to the execution of the model. PSE worked with IRP stakeholders to identify potential new resources, and compiled the relevant information to these resources, such as capital costs, variable costs, transmission needs and output performance. Contracts are not included in this portion of the modeling process, as non-economic contracts are a separate portion of the resource marketplace that cannot be captured in the model.

Optimization Modeling

Optimization modeling is the process of finding the optimal minimum or maximum value of a specific relationship, called the objective function. The objective function in PSE's LTCE model seeks to minimize the revenue requirement of the total portfolio, or, in other words, the cost to operate the fleet of generating resources. An example of a revenue requirement function is outlined below:

The revenue requirement at any given time is defined as:

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

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.

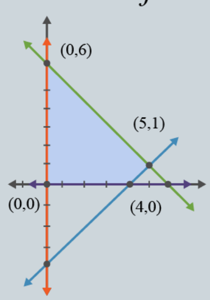
In order to achieve the optimization, various methods may be used including linear programming, integer programming and mixed-integer programming (MIP). AURORA utilizes MIP which is a combination of integer programming and linear programming.

LINEAR PROGRAMMING. Linear programming, also known as linear optimization, is a mathematical model that is represented by linear relationships and constraints. Linear programming is best used to optimize a value that is 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.

A basic example of linear programming, where an objective function C(x,y) is being minimized and maximized:

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

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



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

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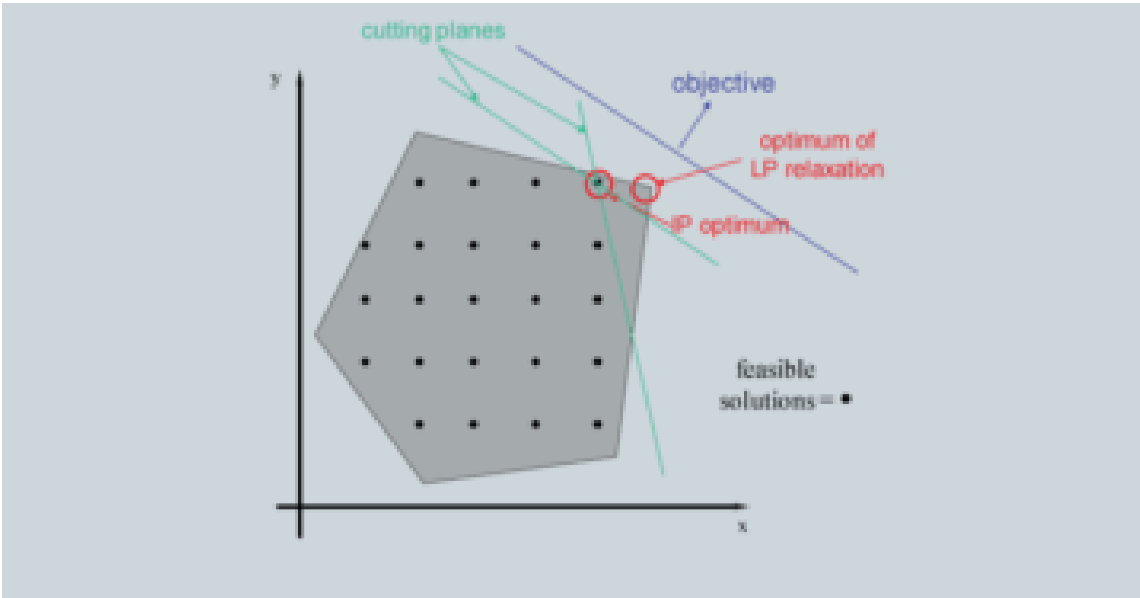
INTEGER PROGRAMMING. Integer Programming is another mathematical optimization method in which some or all of the variables are restricted to integer values. The optimal solution may not be an integer value, but the limitation of the values in the model forces the optimization to produce a solution that 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.

A visual example of an integer programming problem. The optimal solution lies in the grey area, but only solutions that are represented by the black dots are valid:



MIXED INTEGER PROGRAMMING. Mixed integer programming (MIP) refers to a combination of Linear and Integer programming, where a subset of the variables and restrictions take on an integer value. MIP methods are the best suited for handling power system and utility models, as the decisions and restraints faced by utilities are both discrete (how many resources to build, resource lifetimes, how those resources connect to one another) 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. These methods are performed iteratively and include vast amounts of data, which makes the settings used to run the model important in determining the runtime and precision of the solutions.

ITERATIVE SOLVING. When broken down into sets of equations and solving methodologies, the goal of optimization modeling can be deceptively simple. Limitations on computing power, the complexity of the model parameters, and vast amounts of data make a “true solution” impossible to solve for in many cases. In order to work around this, the LTCE model performs multiple iterations in order to converge on a satisfactory answer.

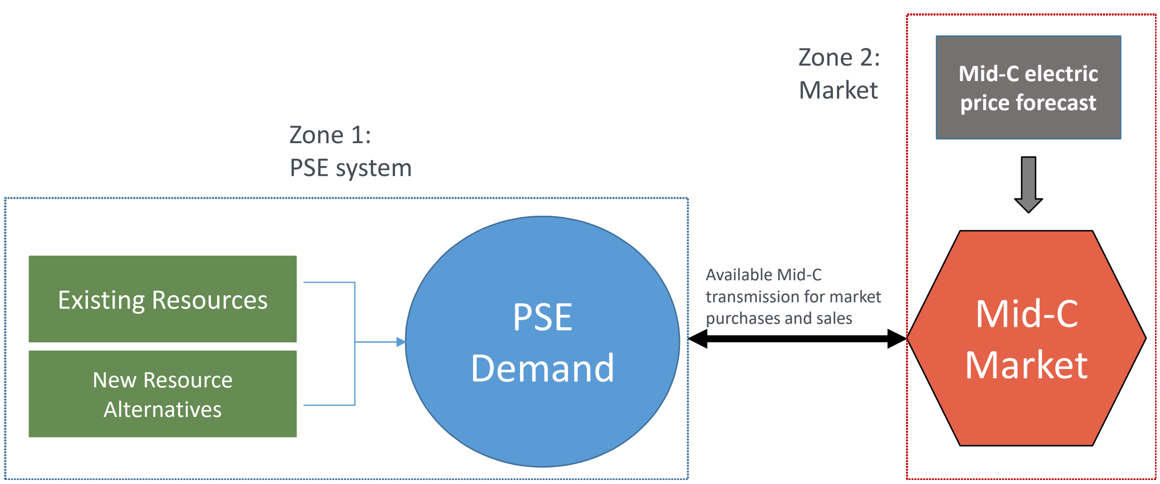
Given the complexity of the model being processed, the model does not produce the same results after each run. Over the course of multiple iterations, AURORA will compare the final portfolios and outputs of each iteration with the previous attempt. If the most recent iteration reaches a certain threshold of similarity to the previous (as determined by the model settings), and has reached the minimum number of iterations, the solution will be considered “converged” and provide it as the final output. If the model has reached the maximum number of iterations (also entered in the model settings), the final iteration will be considered the final output.

System Constraints

The solutions provided by the optimization of the LTCE model seek to provide a path to meeting PSE's load while minimizing the total price of the fleet. Without any constraints, the LTCE optimization model would select the resource that produces the greatest amount of power per dollar spent on the resource and build as many as were needed. This solution is trivial and does not provide any usable insight into how the utility should manage real resources. The addition of constraints allows the model to find a useful solution.

ZONAL CONSTRAINTS. The models use a "zonal model" of transmission, where the model is divided into "zones". The only transmission limits in the standard model are between zones, and PSE does not add more transmission constraints for most simulations due to limitations on runtime and computing power. The zonal model works best for generation optimization. A separate model called the "nodal model" can be used for transmission optimization. Given the current constraints on technology and computing power, there is no integrated model for generation and transmission. Figure G-14, 2 ZONE System, shows how this two-zone system operates in AURORA.

Figure G-14: 2 ZONE System: A graphical example of how PSE's 2-zone system is represented in AURORA, with the zones represented as rectangular boxes and the arrows between them representing transmission links.



For most simulations, PSE operates a two-zone system. This system serves to limit the amounts of market purchases that can be made at any given time as a result of transmission access to the Mid-Columbia market hub.

RESOURCE CONSTRAINTS. Resources in the model are defined by their constraints. A resource needs to be defined by constraints in order 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 installations.
- **Availability** – Resources have a finite lifetime, as well as a “first available” and “last available” year to be installed as a resource. Resources also have scheduled and random maintenance or outage events that are included in the model.

RENEWABLE CONSTRAINTS. The model must meet all legal requirements. The most relevant renewable constraints faced by PSE are related to the Renewable Portfolio Standard (RPS) and the Clean Energy Transformation Act (CETA). The renewable constraints are described in detail in Chapter 5.

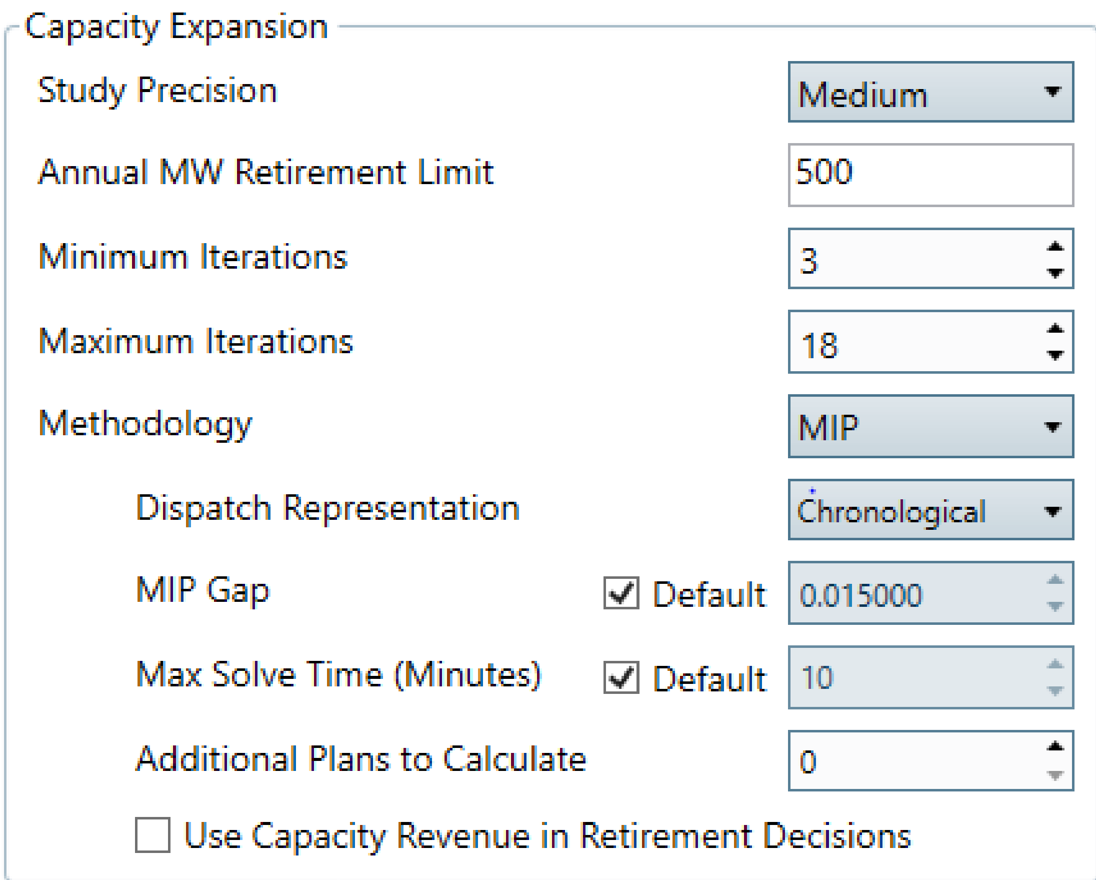
Modeling Settings

The explanations provided for the PSE LTCE models rely heavily on the AURORA documentation provided by Energy Exemplar, and relevant excerpts are included below.

Prior to each individual LTCE model, parameters are set to determine how that simulation will be performed. The default parameters used by PSE are as follows:

Figure G-15: Standard Aurora Parameters for PSE's LTCE Model

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



STUDY PRECISION. During the iterative optimization process, the study precision determines at what point the model determines that a solution has been successfully converged upon. Instead of reaching one "correct answer," the optimization process consists of multiple simulations that gradually converge on an optimized, stable answer given the data that it has. A visual representation of this process shows a model range gradually approaching an optimized solution. In setting a percentage value for the study precision, users determine what is considered "close enough" to the absolute ideal answer. Limitations on runtime and computing power are the main drivers of limiting the precision of a study.

The options for this setting include:

- High: Stops when the changes are less than 0.15 %,
- Medium: Stops when the changes are less than 0.55 %.
- Low: Stops when the changes are less than 2.5 %.

Through experimenting with these settings, PSE has determined that the optimal setting is Medium when considering trade-offs between runtime and precision.

ANNUAL MW RETIREMENT LIMIT. This setting limits the amount of generating capacity that 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. PSE stayed with the default setting of 500 MW as a reasonable maximum for economic resource retirements to prevent any outlier years where vast amounts of resources are being retired.

MINIMUM ITERATIONS*.* This setting specifies the minimum number of iterations that the simulation must complete. PSE sets the minimum to three iterations to ensure that model decisions are being checked.

MAXIMUM ITERATIONS*.* This setting specifies the maximum number of iterations that the simulation must complete. PSE sets the maximum to 18 iterations to ensure that the runtime of the model does not become excessive. A simulation that is taking more than 15 iterations to solve will likely not converge into a usable solution.

METHODOLOGY. AURORA provides two options for this setting: Traditional and MIP. Traditional methodology uses the following steps to perform the simulation, described in the AURORA documentation:

> "Aurora uses the following steps in the Traditional Long-Term Optimization (Capacity Expansion) process:
>
> 1. The first iteration begins with resources selected to meet the planning reserve margins for the zones and pools being run. If reserve margin targets are not being used, the model will assume a reserve margin of the minimum of 0% as the beginning first year reserve margin for each pool and zone. The model will make the first iteration build decisions based on the new resource fixed costs.
> 2. Aurora enumerates all new resources.
> 3. The value for each existing resource is determined.
> 4. The value for each new enumerated resource is determined.
> 5. Resources are sorted by value."

This methodology is a faster method for handling relatively simple simulations, but results in longer runtimes for more complicated portfolios.

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 model that leads to faster convergence times, more optimal (lower) system costs, and better handling of complex resource constraints. PSE employs 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. PSE often uses these settings at their default values, which are calculated based on the amount of data that has been read into the AURORA input database for the simulation. The options are described in the AURORA documentation and are explained in Figure G-16:

Figure G-16: 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 as well as energy, ancillary, and other revenue. The method seeks to select the resources that provide the most value to the system given the constraints. The formulation also includes internal constraints to limit the amount of changes in system capacity that can happen between each iteration. These are dynamically updated to help guide the solution to an optimal solution and promote convergence. This setting is used by PSE for the LTCE modeling process.
MIP Gap	Percentage as a decimal value	This setting controls the precision level tolerance for the optimization. Using the Default setting is generally recommended and will dynamically assign the MIP gap tolerance to be used based on the study precision, objective setting, and potential the size of the problem. 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 used for each of the LT MIP solves. 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 Default is not selected, a user-specified value can be entered. Note that if the time limit is reached, this may mean that results will not be perfectly reproducible, so generally a higher value is recommended.
Additional Plans to Calculate	Integer Value	When this value is greater than zero, AURORA will calculate additional plans after the final new build options and retirements have been determined. To do this a constraint is added 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.

ASSUMPTIONS FOR ALL AURORA MODELS. The LTCE modeling process is a subset of the simulations that PSE performs in AURORA. PSE keeps most of these settings consistent across all models in AURORA, including the LTCE process. Some adjustments may be made for sensitivities or simulations that are not converging properly. Figure G-17 describes the other settings used in AURORA.

Figure G-17: The General Settings Used in all AURORA Models

Setting	Value Type	Definition
Economic Base Year	Year	The dollar year that all currency is set to in the simulation. For consistency, PSE uses 2012 across all simulations through all IRP processes in AURORA. This is the reason that PSE converts all inputs into 2012$.
Resource Dispatch Margin	Percentage	A value used to specify the margin over the cost of the resource required to operate that resource. PSE sets this value to 5%.
Remove Penalty Adders from Pricing	Binary	When this switch is selected, the model will adjust the zonal pricing by removing the effect of the non-commitment penalty on uncommitted resources as well as the minimum generation back down penalty on committed or must run resources. These penalty adders are used 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. PSE selects this setting.
Include Variable O&M in Dispatch	Binary	This option is used to control the treatment of variable operation and maintenance (O&M) expense. If selected, the variable O&M expense will be included in the dispatch decision of a resource. PSE selects 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. PSE selects this setting when modeling CO_2 price as a dispatch cost.
Use Operating Reserves	Binary	This option determines whether the dispatch will recognize operating reserve requirements and identify a set of units to be used for operating reserve purposes. When this option is selected the model will select a set of units (when possible) to meet the requirement. PSE selects 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. PSE selects this setting.

Resource Value Decisions

When solving for each time step of the LTCE model, AURORA considers the needs of the portfolio and the resources that are available to fill those needs. The needs of the portfolio include capacity need, reserve margins, effective load carrying capacity (ELCC) and other relevant parameters that dictate the utility's ability to provide power. If a need must be addressed, the model will select a subset of resources that are able to fill that need.
At that time step, each resource will undergo a small simulation to forecast how it will fare in the portfolio. This miniature forecast takes into account the operating life, capacity output and scheduled availability of the resource. Resources that are best able to fulfill the needs of the portfolio are then considered on the merits of their costs.

Resource costs include the cost of capital to invest in the resource, fixed operation and maintenance (O&M) costs, and variable O&M costs. Capital costs include the price of the property, physical equipment, transmission connections and other investments that must be made to acquire the physical resource. Fixed O&M costs include the costs of staffing and scheduled maintenance of the resource under normal conditions. Variable O&M costs include costs that are incurred by running the resource, such as fuel costs and maintenance issues that accompany use.

Once the costs of operating each resource are forecasted, they are compared to find which has the least cost while serving the needs of PSE. The goal of the LTCE model, an optimization model, is to provide a portfolio of resources that minimizes the cost of the portfolio.

Modeling Inputs

A number of input assumptions are necessary to parameterize the model. These assumptions come from a mix of public and proprietary sources and some are refined through PSE's stakeholder engagement process.

FORECASTS. Some attributes of the model cannot be captured 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. To help provide these types of information into the model, a series of forecasts are included in the input assumptions. Forecasts help to direct overall trends of what will be affecting 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.

Figure G-18: Forecast Inputs and Sources

Input	Source	Description
Demand Forecast	Internal (see Chapter 6 and Appendix F)	Energy and peak demand forecast for PSE territory over the IRP planning horizon.
Electric Price Forecast	Internal (See Chapter 5 and above)	Output of the AURORA Electric Power Price Model.
Natural Gas Price Forecast	Forward Marks prices, Wood Mackenzie (see Chapter 5)	A combination of the Forward Marks prices and Wood Mackenzie long term price forecast.
Wind and Solar Generation	Internal PSE forecasts, NREL, resource developers	Solar and wind generation shapes dictate the performance of these renewable resources. Some forecasts are provided by PSE from existing wind projects. As a result of stakeholder recommendations, NREL data is used.

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

Existing Resources: Existing resources are provided to the model as the base portfolio. Existing resources include resources that are already in operation and resources that are scheduled to be in operation in the future. Scheduled maintenance and outage dates, performance metrics and future retirement dates are provided to the model.

Generic Resources: Generic resources are the resources that are available to be added to the LTCE model. These resources are representations of real resources that may be acquired by the utility in the future. Information about the generic resources include the fuel used by the resources, costs and availability. Transmission information is also included based on the locations of the resources being modeled. Details of the generic resources modeled by PSE are included in Appendix D, and the final generic resource inputs are available in Appendix H. Simplifications are made to these resources in order to obtain representative samples of a certain resource group. For example, the modeling of every potential site that PSE may acquire a solar project would require prohibitive amounts of solar data from each individual location. To work around this issue, a predetermined site from different geographic regions to represent a solar resource in that area is used.

The specific generic resource characteristics have been developed in partnership with IRP stakeholders. As a result of stakeholder feedback, the costs of multiple resources were changed to reflect more current price trends, and new resources were added such as renewable/energy storage hybrid resources.

CAPITAL COST CALCULATIONS. The capital cost of a resource plays a large role in their consideration for acquisition by the model. However, the capital cost of a resource is not a one-time investment made at the time of acquisition. PSE must typically go into debt to obtain the purchasing power necessary to acquire a resource.

Every resource, once installed, has its own "revenue requirement." This revenue requirement is the amount of money that the utility must collect from ratepayers in order to cover the operating expenses of the resource in addition to the financing costs of the capital investment. The combined revenue requirement of all resources in the portfolio is the portfolio's total revenue requirement, which is the objective function that the LTCE model seeks to minimize.

The revenue requirement is broken down in the following equation:

$$\textbf{Revenue Requirement} = (\textbf{Rate Base} * \textbf{Rate of Return}) + \textbf{Operating Expenses}$$

Where:

The **Rate Base** is the amount of investment made in the plant devoted to the operating capacity of that plant. In the state of Washington, the **Rate Base** is valued as the original cost of the resource, minus the accumulated financial depreciation and deferred tax payments on the resource.

The **Rate of Return** is the predetermined return on investment that a utility will earn from payments made by ratepayers. When the **Rate Base** is multiplied by the **Rate of Return,** the result is the operating income requirement of the plant, which represents a combination of the capital costs and fixed O&M costs of the resource.

Operating Expenses of a resource are the variable O&M costs of that resource, including fuel and maintenance as a result of plant operation.

SOCIAL COST OF GREENHOUSE GASES. Per CETA requirements, PSE is including the social cost of greenhouse gases (SCGHG) as a cost adder as a part of the IRP process. PSE is modeling the SCGHG as a **planning adder**. However, PSE completed several portfolio sensitivities and electric price scenarios modeling the SCGHG as a variable dispatch cost as requested by stakeholders.

PSE models the SCGHG as a planning adder using the following methodology:

1. The LTCE model is run to determine portfolio build decisions over the modeling timeframe. Within the LTCE model, the SCGHG is applied as a penalty to emitting resources (i.e., fossil-fuel fired resources) during each build decision.

    a. The planning adder is calculated as such:
        i. AURORA generates a forecast of dispatch for the economic life of the emitting resource. This dispatch forecast is not impacted by the SCGHG to simulate real-world dispatch conditions.
        ii. The emissions of this dispatch forecast are summed for the economic life of the emitting resource and the SCGHG is applied to the total lifetime emissions.
        iii. The lifetime SCGHG is then applied as and adder that is amortized over the life of the project.
        iv. A new build decision is made based on the total lifetime cost of the resource.

2. The LTCE model results in a portfolio of new builds and retirements. Since the LTCE runs through many simulations a sampling method is used to decrease run time, so the final step is to pass the portfolio to the hourly dispatch model, which is capable of modeling dispatch decisions at a much higher time resolution. The hourly dispatch model is not capable of making build decisions, but will more accurately assess total portfolio cost to rate payers. Since the SCGHG is not a cost passed to rate payers, the SCGHG is not included as part of this modelling step.

Stakeholders have requested that the SCGHG be included as a **dispatch cost** at all modeling levels. PSE understands this approach as:

1. A long-term capacity expansion (LTCE) model is run to determine portfolio build decisions over the modeling timeframe. Within the LTCE model, the SCGHG is applied as a penalty to emitting resources during each build decision as a dispatch cost. This means that the total energy produced by the resource has decreased due the higher cost of dispatch.
2. The LTCE model results in a portfolio of new builds and retirements. Since the LTCE runs through many simulations a sampling method is used to decrease run time, so the final step is to pass the portfolio to the hourly dispatch model, which is capable of modeling dispatch decisions at a much higher time resolution. The hourly dispatch

model is not capable of making build decisions, but will more accurately assess total portfolio cost to rate payers. The SCGHG can either

a. be included in dispatch decisions to remain consistent with the LTCE model, or
b. not be included in the hourly dispatch.

PSE used the SCGHG as a **planning adder** for the LTCE simulations. However, PSE completed some portfolio sensitivities using the SCGHG as a **dispatch cost.** These portfolio sensitivities are included in Chapter 8.

FINANCIAL ASSUMPTIONS. As the portfolio modeling process takes place over a long-term timeline, assumptions must be made about the financial system that the resources will operate in.

Production Tax Credit Assumptions: The PTC is phased down over time: 100 percent in 2020, 80 percent in 2021, 60 percent in 2022, 40 percent in 2023, 60 percent in 2024 and 0 percent thereafter for projects with respective online dates. A project must have started before the end of 2020 and has four years to complete to receive the PTC. For projects for which construction started in 2016 & 2017, the online dates have been extended by an additional year to 2021 and 2022 respectively with 100 percent and 80 percent remaining unchanged. A project must meet the physical work test or show that 5 percent or more of the total cost of the project was paid during that construction-begin year. For example, if a project began construction or paid 5 percent or more in costs in the year 2020, it will receive the 60 percent PTC even if the facility doesn't go online until 2024. The PTC is received over 10 years and is given as a variable rate in dollars per MWh. All PTC values and eligibility are based on Congressional Research Service publication dated April 29, 2020, The Renewable Electricity Production Tax Credit: In Brief.

Investment Tax Credit Assumptions (ITC): The ITC is a one-time benefit based on the total capital cost invested in the project. The phase-down over time varies depending on the technology:

- Solar: 30 percent 2020-2023, 26 percent in 2024, 22 percent in 2025, and 10 percent in 2026 and thereafter.

The ITC benefit is based on the year that the project is complete. A project has four years to complete to receive the ITC. For example, if a solar project starts construction in 2021 but does not go online until 2025, it will receive a 22 percent tax credit based on the total capital cost. So, if the project costs $300 million, then the developer will receive $66 million in tax benefits.

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

Inflation Rate: The 2017 IRP uses a 2.5 percent escalation for all assumptions unless otherwise noted. This is the long-run average inflation rate that the AURORA model uses.

Transmission Inflation Rate: In 1996, the BPA rate was $1.000 per kW per year and the estimated total rate in 2015 is $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.

Gas Transport Inflation Rate: Natural gas pipeline rates are not updated often and recent history indicates that the rates are 0 percent. PSE has assumed zero inflation on pipeline rates because the major pipelines on which we operate have declining rate bases and major expansions will be incrementally priced. Growth in cost of service from operating costs and maintenance capital additions are expected to be offset by declines due to depreciation.

Transmission and Distribution (T&D) Costs: A transmission and distribution deferral value of $15.15/kW-year was included as a negative cost item in the resource value for distributed battery energy storage, demand response and demand-side resources. This is an internal PSE calculated number based on current project costs.

Model Documentation

As of September 2020, the version of AURORA being used by PSE is Aurora 13.4.1001.

An excerpt from the AURORA documentation:

Mathematical Framework (Risk Metric = Variance)

This next section describes the mathematical framework for the optimization in greater detail. It lays out how portfolio cost and risk are defined and how the LPs are performed to find the portfolios along the efficient frontier. For the notation in this section, assume that the word “resource” refers to either an Aurora resource or portfolio contract, and that the term “time period” refers to a specific time bucket as already explained above.

Portfolio Notation

Assume the following general notation:

1. There exist *r* candidate portfolio resources over *m* time periods.
2. For a portfolio selected from the set of *r* resources, the proportion of resource *j* held in the portfolio is denoted a_j. In this context, each a_j must lie in the unit interval, i.e. $\forall j, a_j \in [0, 1]$.
3. $\underline{a}$ is the column vector $(a_1, a_2, \ldots, a_r)'$.
4. *I* is an identity matrix, with dimension indicated by context.
5. $E_{\alpha\beta}$ is an *α* by *β* array of 1s.

From each individual Aurora simulation, assume the following notation:

- In time period *i*, resource *j* has a total cost C_{ij}. This includes fuel costs, emissions costs, variable O&M costs, startup costs, and fixed costs.
- Resource *j* may also have capacity revenue in period *i,* denoted as RK_{ij}.
- The energy generated in period *i* by resource *j* is denoted G_{ij}.
- Portfolio demand in period *i* is denoted D_i.
- Portfolio capacity demand (annual peak demand) in year *y* is denoted DK_y.
- Average market price in period *i* is denoted p_i.
- Average capacity price in year *y* is denoted PK_y.
- Denote the following arrays:
  - RK is an *m* by *r* matrix, $\{RK_{ij}\}$.
  - G is an *m* by *r* matrix, $\{G_{ij}\}$.
  - $\underline{p}$ is the column vector $(p_1, p_2, \ldots, p_m)'$.
  - $\underline{PK}$ is the column vector $(PK_1, PK_2, \ldots, PK_m)'$.
  - $\underline{D}$ is the column vector $(D_1, D_2, \ldots, D_m)'$.
  - $\underline{DK}$ is the column vector $(DK_1, DK_2, \ldots, DK_m)'$.

With this notation, a portfolio is a triplet of values for the vectors $\underline{a}$, $\underline{D}$ and $\underline{DK}$. For Aurora portfolio optimization, $\underline{a}$ is the only one of the three variables subject to adjustment, $\underline{D}$ and $\underline{DK}$ being fixed (as calculated from the output data). Thus $\underline{a}$ becomes the vector of decision variables which will ultimately be solved for by the linear program when each portfolio is derived.

Defining Portfolio Cost and Variance

The total net cost of a portfolio in a run can be defined as the sum of four parts:

1. The cost of holding shares of resources held in the portfolio: $E_{1m}C\underline{a}$
2. The cost of market transactions required to balance the portfolio demand with the energy production of the resource shares held in the portfolio: $\underline{p}'(\underline{D} - G\underline{a})$
3. Optionally, if capacity prices and revenues are used, the cost of capacity corresponding to the portfolio demand: $\underline{PK}'\,\underline{DK}$
4. Optionally, if capacity prices and revenues are used, the negative capacity revenues from shares of resources held in the portfolio: $E_{1m}(RK)\underline{a}$

Thus the net portfolio cost *B* is:

$$B = E_{1m}C\underline{a} + \underline{p}'(\underline{D} - G\underline{a}) + \underline{PK}'\underline{DK} - E_{1m}(RK)\underline{a}\text{, or}$$

$$B = \left(E_{1m}(C - RK) - \underline{p}'G\right)\underline{a} + \underline{p}'\underline{D} - \underline{PK}'\underline{DK}$$

Define the vector $\underline{NC}'$ as $E_{1m}(C - RK) - \underline{p}'G$, and the final cost equation becomes

$$B = \underline{NC}'\underline{a} + \underline{p}'\underline{D} - \underline{PK}'\underline{DK}$$

There are three terms on the right side of this equation, only one of which involves $\underline{a}$. To simplify the relevant algebra, write the three terms as:

$$A_1 = \underline{NC}'\underline{a}$$

$$A_2 = \underline{p}'\underline{D}$$

$$A_3 = \underline{PK}'\underline{DK}.$$

Then the total portfolio cost can be written as:

$$B = A_1 + A_2 + A_3$$

The total portfolio variance can be written as *Var*(*B*) =

$$Var(A_1) + Var(A_2) + Var(A_3) + 2Cov(A_1, A_2) + 2Cov(A_1, A_3) + 2Cov(A_1, A_3)$$

Optimization Objective Functions

The optimization will use both cost and variance as objective functions for the linear program, so we need to be able to formulate both of these as a linear function of the decision variables vector a.

To do this for portfolio cost, we need to find the expected values which make up equation 1. The total expected portfolio cost becomes:

$$E[B] = E\left[\underline{NC}'\underline{a} + \underline{p}'\underline{D} - \underline{PK}'\underline{DK}\right] = E[\underline{NC}']\underline{a} + E\left[\underline{p}'\underline{D}\right] - E[\underline{PK}'\underline{DK}]$$

All the expected values in this expression are estimated by taking averages of the terms in brackets across the set of underlying Aurora runs. Note that when only one run has been performed, these expected value terms are simply the values from that run.

To describe the total portfolio variance as a linear function of a, we can expand equation 2 as follows:

$$Var(A_1) = \underline{a}'Cov(NC'E_{m1})\underline{a} \tag{4}$$

$$Var(A_2) = Var\left(\underline{p}'\underline{D}\right) \tag{5}$$

$$Var(A_3) = Var(\underline{PK}'\underline{DK}) \tag{6}$$

$$2Cov(A_1, A_2) = 2\left(E_{1m}Cov\left(\underline{p}'\underline{D}, C\right)\underline{a} - E_{1m}Cov\left(\underline{p}'\underline{D}, RK\right)\underline{a} - Cov\left(\underline{p}'\underline{D}, \underline{p}'G\right)\underline{a}\right) \tag{7}$$

$$\begin{gathered} 2Cov(A_1, A_3) = \\ 2\left(E_{1m}Cov(\underline{PK}'\underline{DK}, C)\underline{a} - E_{1m}Cov(\underline{PK}'\underline{DK}, RK)\underline{a} - Cov\left(\underline{PK}'\underline{DK}, \underline{p}'G\right)\underline{a}\right) \end{gathered} \tag{8}$$

$$2Cov(A_1, A_3) = 2Cov\left(\underline{p}'\underline{D}, \underline{PK}'\underline{DK}\right) \tag{9}$$

The estimated variance of a scalar, such as in equations 5 and 6 above, is the sample variance of its value over the underlying Aurora runs. When vectors appear in the Cov() notation, the result is the estimated covariance matrix found by using the iterative data from the underlying Aurora runs. When two different arguments appear in Cov(), the implied covariance matrix will be d1-by-d2, where d1 is the length of the first vector argument, and d2 the length of the second. When the variance values are calculated, the unbiased sample estimate is always used.

Equation 4 is in a quadratic form which must be further transformed as a linear function of new decision variables. A linear approximation method using matrix diagonalization as well as a concept known as the principle of adjacent weights is used to be able to express Var(A1) as a linear function of a and other newly defined decision variables. The details of this technique are not delineated here. Testing has shown that the approximation technique used generally differs by less than .01% from the actual quadratic variance calculation.

AURORA Stochastic Risk Model

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 IRP process, 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 IRP, PSE modeled 27 sensitivities with a total of 37 portfolios which allowed PSE to evaluate a broad range of resource options and associated costs and risk. The sensitivity analysis is a type of risk analysis. By varying one parameter, we can isolate out how that one variable changes the portfolio builds and costs.

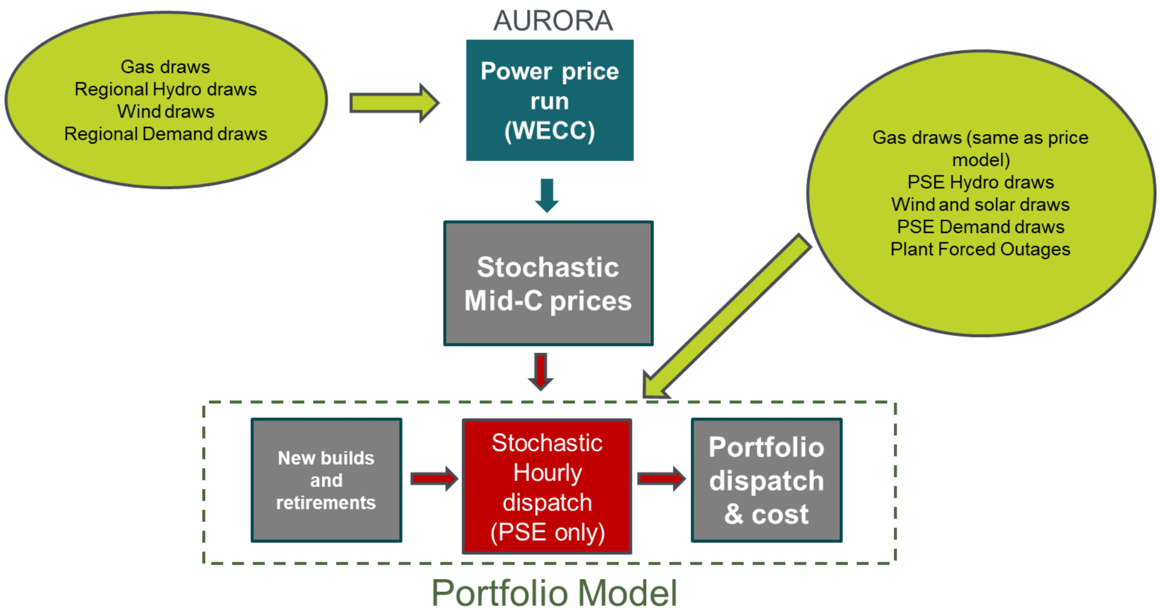
Stochastic risk analysis deliberately varies the static inputs to a deterministic analysis, to test how a portfolio developed in the deterministic analysis performs with regard to cost and risk across a wide range of potential future power prices, natural gas prices, hydro generation, wind generation, loads and plant forced outages. By simulating the same portfolio under different conditions, more information can be gathered about how a portfolio will perform in an uncertain future. The stochastic portfolio analysis is performed in AURORA.

The goal of the stochastic modeling process is 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 hydro, etc., 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 are used to generate a distribution of resource energy outputs (dispatched to prices and must-take), costs and revenues from AURORA. The stochastic inputs considered in this IRP 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.

Development of Stochastic Model Inputs

A key goal in the stochastic model is to be able to capture the relationships of major drivers of risks with the stochastic variables in a systematic way. One of these relationships, for example, is that variations in electric power prices should be correlated with variations in natural gas prices, contemporaneously or with a lag. Figure G-19 shows the key drivers in developing these stochastic inputs. In essence, long-term economic conditions and energy markets determine the variability in the stochastic variables.

Figure G-19: The Major Components of the Stochastic Modeling Process



PSE's stochastic model follows this process to simulate 310 futures of portfolio dispatch and cost.

1. The first step in PSE's stochastic process is generating electric price draws. Similar to the generating the deterministic wholesale price forecast, PSE uses Energy Exemplar's AURORA model to simulate resource dispatch to meet demand and various system constraints. Regional demand, gas price, hydro generation and wind generation are varied to generate the electric price draws. PSE uses the price forecast for the "Mid-C" zone as the wholesale market price in the portfolio model.
2. Next, we move to PSE's hourly portfolio dispatch model. The electric prices and natural gas price draws generated in the first step are pulled into the portfolio model.
3. PSE takes different portfolios (drawn from the deterministic scenario and sensitivity portfolios) and runs them through 310 draws that model varying power prices, gas prices, hydro generation, wind generation, solar generation, load forecasts (energy and peak) and plant forced outages. From this analysis, PSE can observe how robust or risky the portfolio may be and where significant differences occur when risk is analyzed.

Stochastic Electric Price Forecast

PSE uses Aurora, a production cost model that utilizes electric market fundamentals to generate the electric price draws. Aurora offers a Monte Carlo Risk capability that allows users to apply uncertainty to a selection of input variables. The variability of input assumptions can either be introduced into the model as an external data source or Aurora can generate samples based on user statistics on a key driver or input variable. This section describes the model input assumptions that were varied to generate the stochastic electric price forecast.

NATURAL GAS PRICES. PSE relied on the Aurora's internal capability to specify distributions on select drivers, in this case gas prices, to generate samples from a statistical distribution. The risk factor represents the level of adjustment to the base value for the specified variable for the relevant time period. To calculate the risk factor on gas prices, PSE calculated the correlation of gas prices from Sumas, Rockies (Opal), AECO, San Juan, Malin, Topock, Stanfield and PGE City Gate to Henry Hub using data from Wood Mackenzie's Spring 2020 Long Term View Price Update. The Low, Medium, and High gas prices were also evaluated for each hub to determine the average and standard deviation for each calendar month. The standard deviation as a percent of the mean for each calendar month and is used as an input to AURORA for risk sampling. Figure G-20 and G-21 below illustrate the annual draws and the levelized 20-year Sumas gas price $/mmbtu generated by the Aurora model.

Figure G-20: Annual Sumas Gas Price Draws ($/mmBtu)

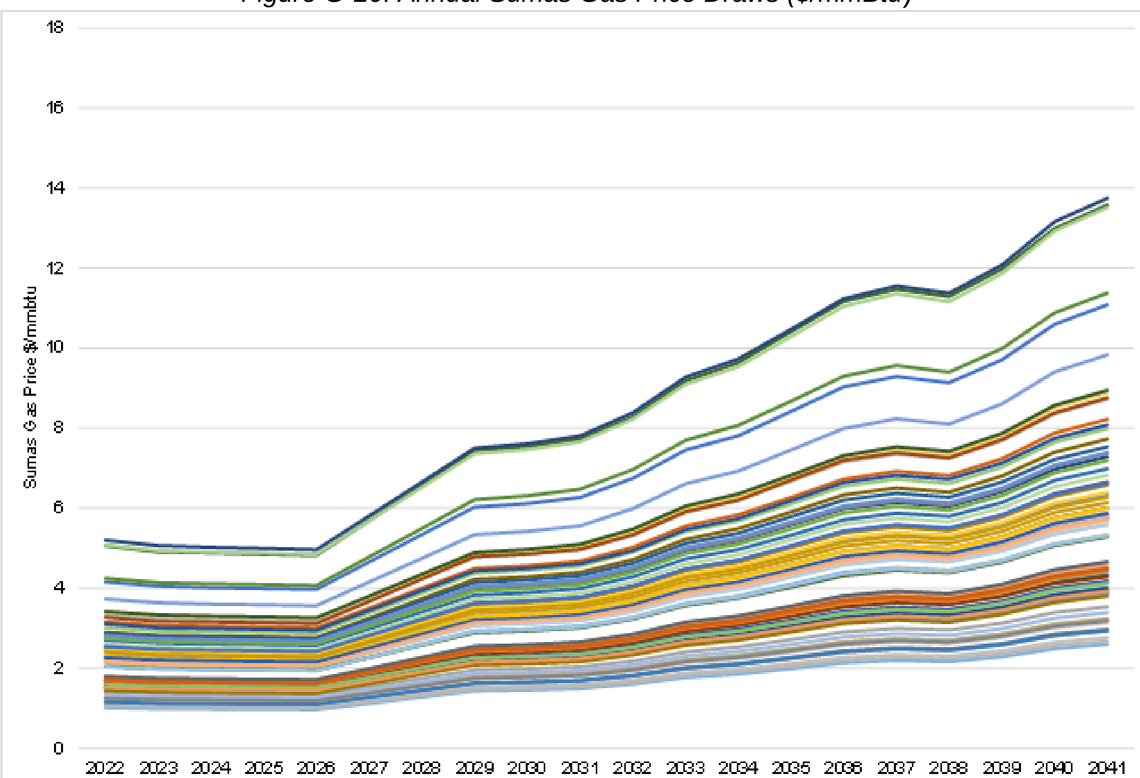
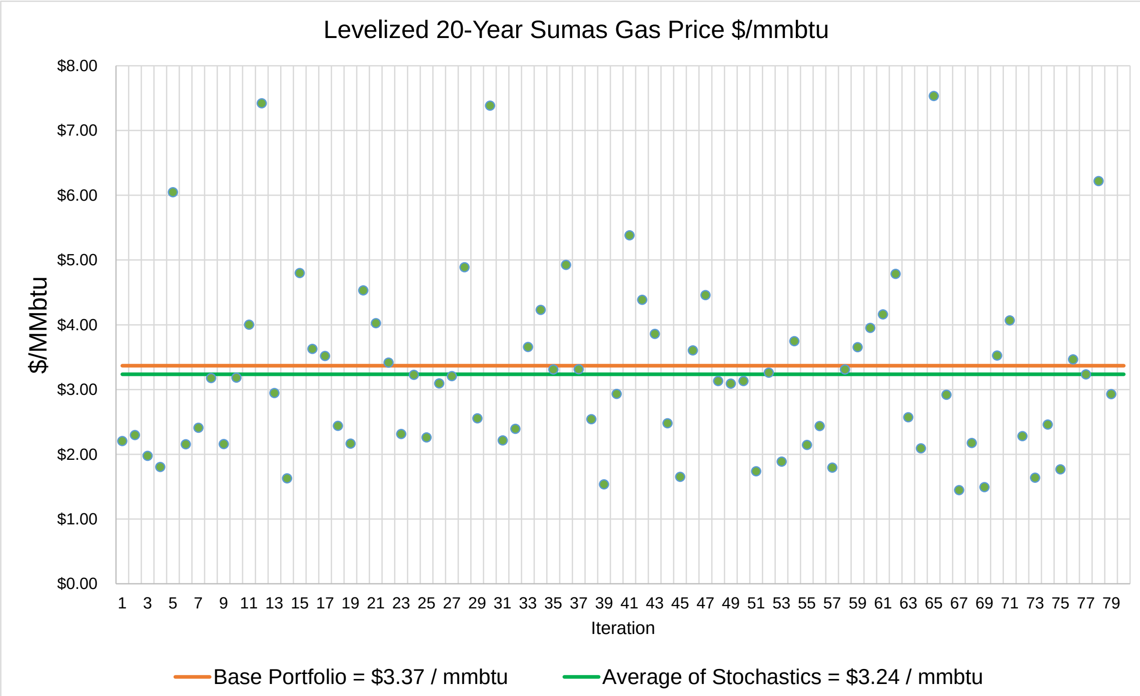


Figure G-21: Levelized 20-year Sumas Natural Gas Price $/mmbtu

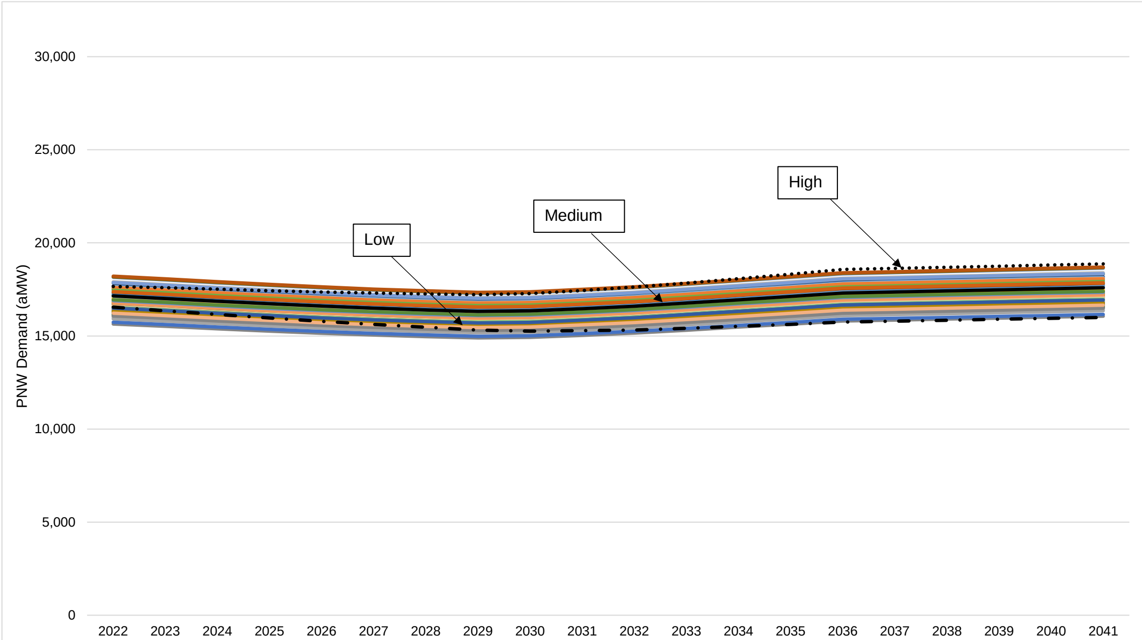


REGIONAL DEMAND. Similar to natural gas prices, PSE relied on the Aurora's internal capability to generate samples from a statistical distribution of demand. Low, Medium, and High regional demand forecasts used in the deterministic price forecasts were evaluated to determine the standard deviation as a percent of the mean for 24 years. Figure G-22: displays the 24-year Levelized Demand and the calculated standard deviation for the region. The standard deviation is used as an input to Aurora for the risk sampling of the entire WECC. Figure G-23 below illustrates the 80 draws of demand generated by Aurora for the Pacific Northwest.

Figure G-22: 24-year Levelized Demand for PNW

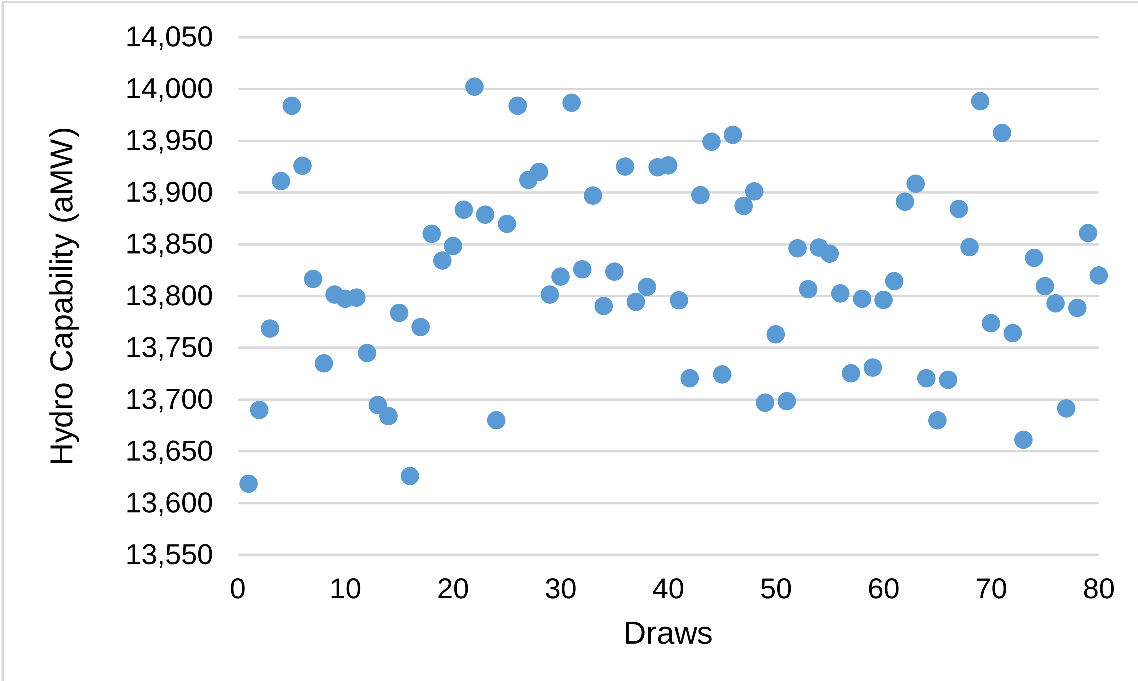
24 Yr Levelized Demand (PNW)	
Low (aMW)	15,820
Medium (aMW)	16,912
High (aMW)	17,833
Mean	16,855
St Dev	1,008
St Dev Pct	0.06

Figure G-23: Pacific Northwest Demand Draws (aMW)



HYDRO VARIABILITY. For the power price stochastics simulations, 80 iterations of possible hydro conditions were taken from the hydro data delivered in Energy Exemplar's default database for the Northwest states, British Columbia and California. The years included in this database are 1929 – 2008. The hydro database is provided by the Bonneville Power Administration (BPA) The BPA releases an updated dataset every 10 years, with the last release from 2012 containing the years 1929 – 2008. The Northwest Power Pool information relating to river operation according to the latest Biological Opinion is implemented. This data is summarized by AURORA Area and adjusted for non-reporting hydro generators. The 80-year hydro capability for the Pacific Northwest can be seen in in Figure G-24.

Figure G-24: Hydro Capability for the Pacific Northwest for 80 Hydro Years, 1929-2008.



WIND VARIABILITY. Energy Exemplar developed wind shapes in the default Aurora database relying primarily on generation estimates from the National Renewable Energy Laboratory's (NREL) Wind Integration National Database (WIND) 2014 Toolkit, using data from the years 2007 – 2012. The generation from clusters of NREL wind sites with similar geography and capacity factors were averaged together to form each of the delivered wind shapes. For each wind region, developed hourly shapes with capacity factors appropriate for each wind class ranging from a high of a 45 percent capacity to a low of a 25 percent capacity factor. For the Power Price Stochastics Run, all available hourly wind shapes for each state in the default database were identified and was the basis of randomly generating 80 iterations of wind data for each location.

STOCHASTIC ELECTRIC PRICE FORECAST RESULTS. AURORA forecasts market prices and operation based on the forecasts of key fundamental drivers such as demand, fuel prices, and hydro conditions. Using the risk sampling for Demand, Fuel and the pre-defined iteration set Hydro and Wind, Aurora is able to generate 80 iterations of power price forecast. PSE runs one price simulation for each of the 80 hydro years, which creates 80 price draws.

For the 2021 IRP, the annual and average power prices of the stochastic Power Price run are shown in Figure G-25 and G-26.

Figure G-25: Annual Power Price Stochastic Results

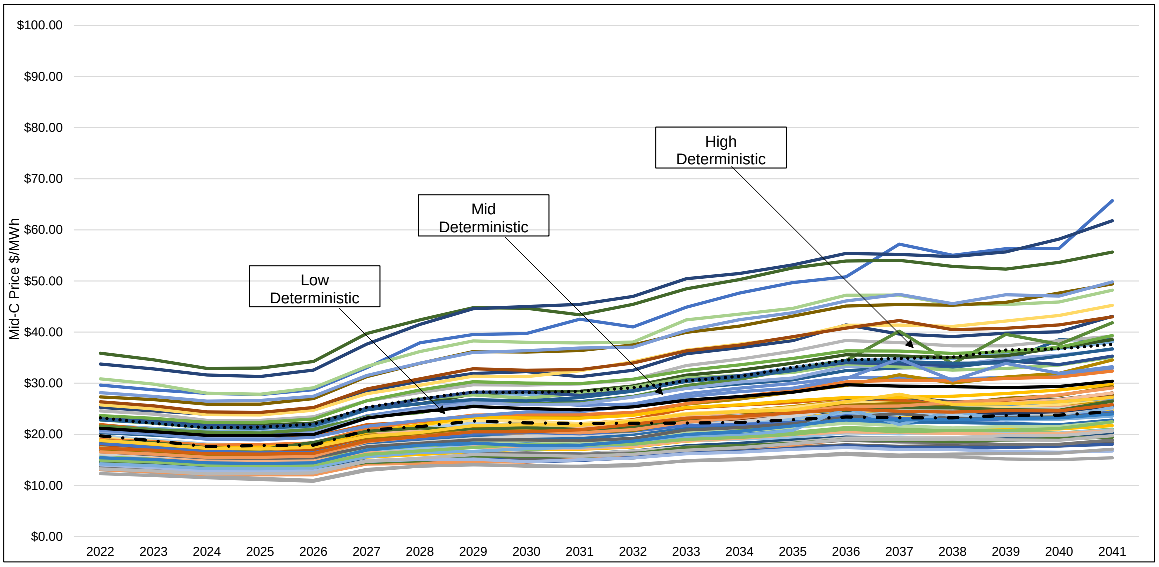
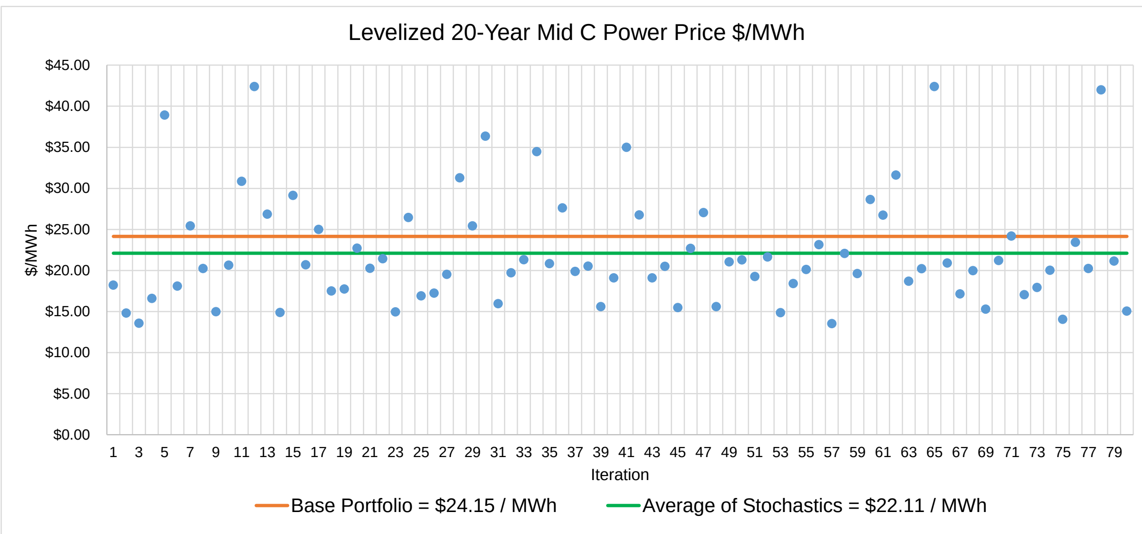


Figure G-26: The Stochastic Power Price Results



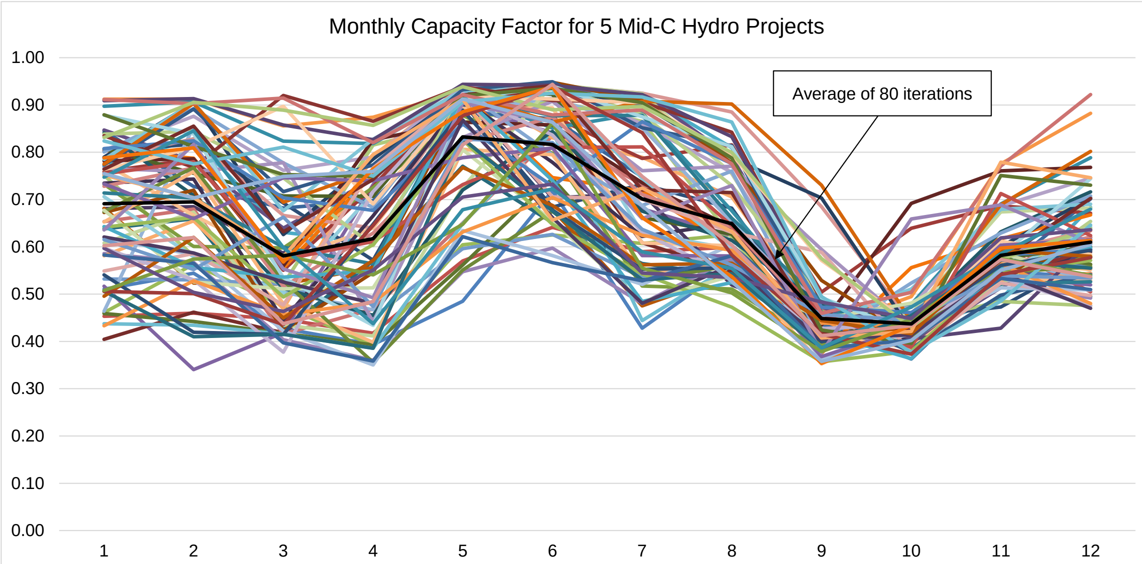
Stochastic Portfolio Model

PSE also uses Aurora for stochastic portfolio modeling and applies a pre-defined iteration set to modify the input data in the model. PSE take the portfolios (drawn from the deterministic scenario and sensitivity portfolios) and runs them through 310 draws that model varying power prices, gas prices, hydro generation, wind generation, solar generation, load forecasts (energy and peak), and plant forced outages. This section describes the model input assumptions that were varied to generate the portfolio dispatch and cost.

ELECTRIC AND NATURAL GAS PRICE. Electric price and natural gas inputs were discussed in the previous section. Each completed set of power prices is packaged with gas price and hydro inputs assumed when generating that particular power price forecast. This bundle of power prices, gas prices, hydro conditions are used as a set of inputs into the Stochastic Portfolio Model. By packaging the power price, gas price and hydro year together relationship between gas prices and Mid-C prices and the relationship between hydro and power prices are preserved. Since there are only 80 draws generated from Stochastic Electric Price Forecast, the electric price and natural gas were repeated 4 times to generate 310 draws.

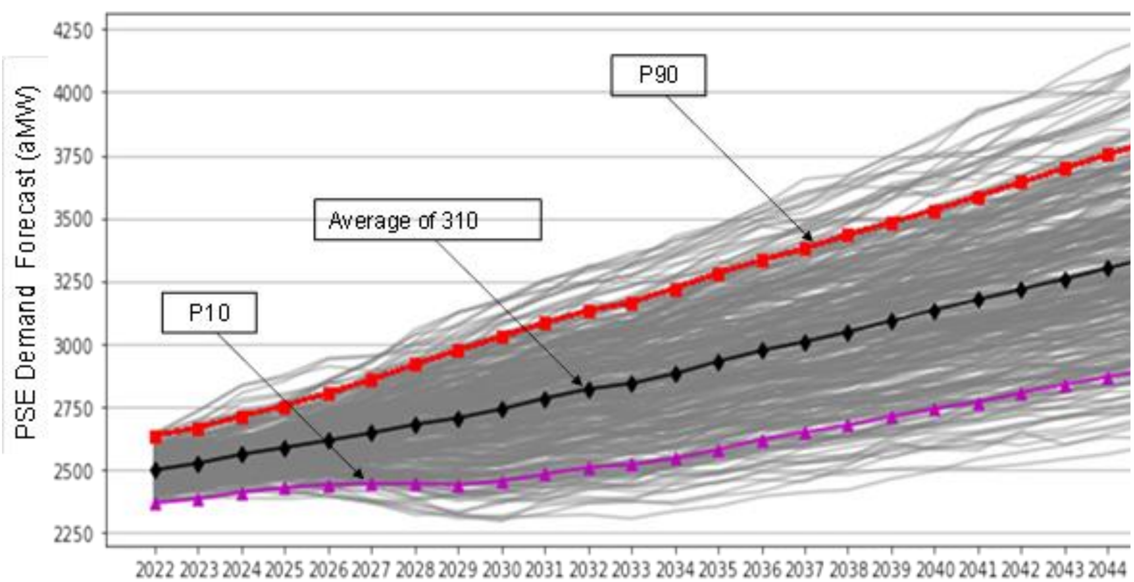
HYDRO VARIABILITY. PSE uses the same hydro data that was developed by the Bonneville Power Administration and used in BPA's rate cases. It is also the same hydro data that is used by the Northwest Power and Conservation council along with all the other utilities in the Pacific Northwest. BPA releases an updated dataset every 10 years of the natural streamflow data, with the last release from 2012 containing the years 1929 – 2008. While the natural streamflow data is only updated once every 10 years, a bi-annual study is performed to update for planned outages and any new or revised non-power restrictions and obligations (fish spill requirements, flood control elevations, etc.). The 80-year Mid-C Hydro data used in this study is also the same dataset used for PSE's 2020 Power Cost Only Rate Case. It is important to stay consistent with the other entities since we are all modeling the same hydro power projects. PSE in particular does not have a large dependence on owned or contracted hydro resources, so variations have a smaller effect on PSE's ability to meet demand. The hydro variations have a larger effect on the available market for short term purchases which is captured in the market risk assessment. Hydro output of all 80 hydro years can be seen in in Figure G-27. 80 hydro years is equivalent to 80 iterations and repeated 4 times to generate 310 draws.

Figure G-27: Hydro Output for All 80 Hydro Years, 1929-2008



PSE DEMAND. To generate the set of stochastic electric demand forecasts, the demand forecasts assume economic/demographic, temperature, electric vehicle and model uncertainties. The high and low demand forecasts are derived from the distribution of these stochastic forecasts at the monthly and annual levels. *A full explanation of the stochastic demand forecasts can be found in Appendix F, Demand Forecasting Models.* A comparison of all demand forecasts used in the stochastic modeling process can be found in Figure G-28.

Figure G-28: Demand Forecast Simulations – Annual Energy (aMW)



SAMPLING GENERIC WIND AND SOLAR SHAPES. For each generic solar and wind resource modeled in the 2021 IRP, 252 production curves were created from the years 2007-2012. The sets of production curves contain 42 curves from each year in order to allow correlated sampling across renewable outputs. For the deterministic modeling process, a representative curve was selected from each dataset to model the performance of a generic renewable resource. In the stochastic modeling process, each renewable resource will operate with a unique production curve drawn from the set 252. Across all renewable resources, the generation year is the same within an iteration. The consistency of the generation year allows the renewable generation to preserve large-scale weather trends that may affect multiple locations at once.

To create the 310 stochastic input sets, each of the 252 sets of renewable shapes was used. Once the first 252 stochastic input sets had been created, the first 58 sets of renewable shapes were reused to complete the rest of the stochastic inputs. Figure G-29 and G-30 show the seasonal capacity factors of the wind and solar curves. A full description of the wind and solar curves can be found in Appendix D.

Figure G-29: The Seasonal Capacity Factors of All Generic Wind Resources

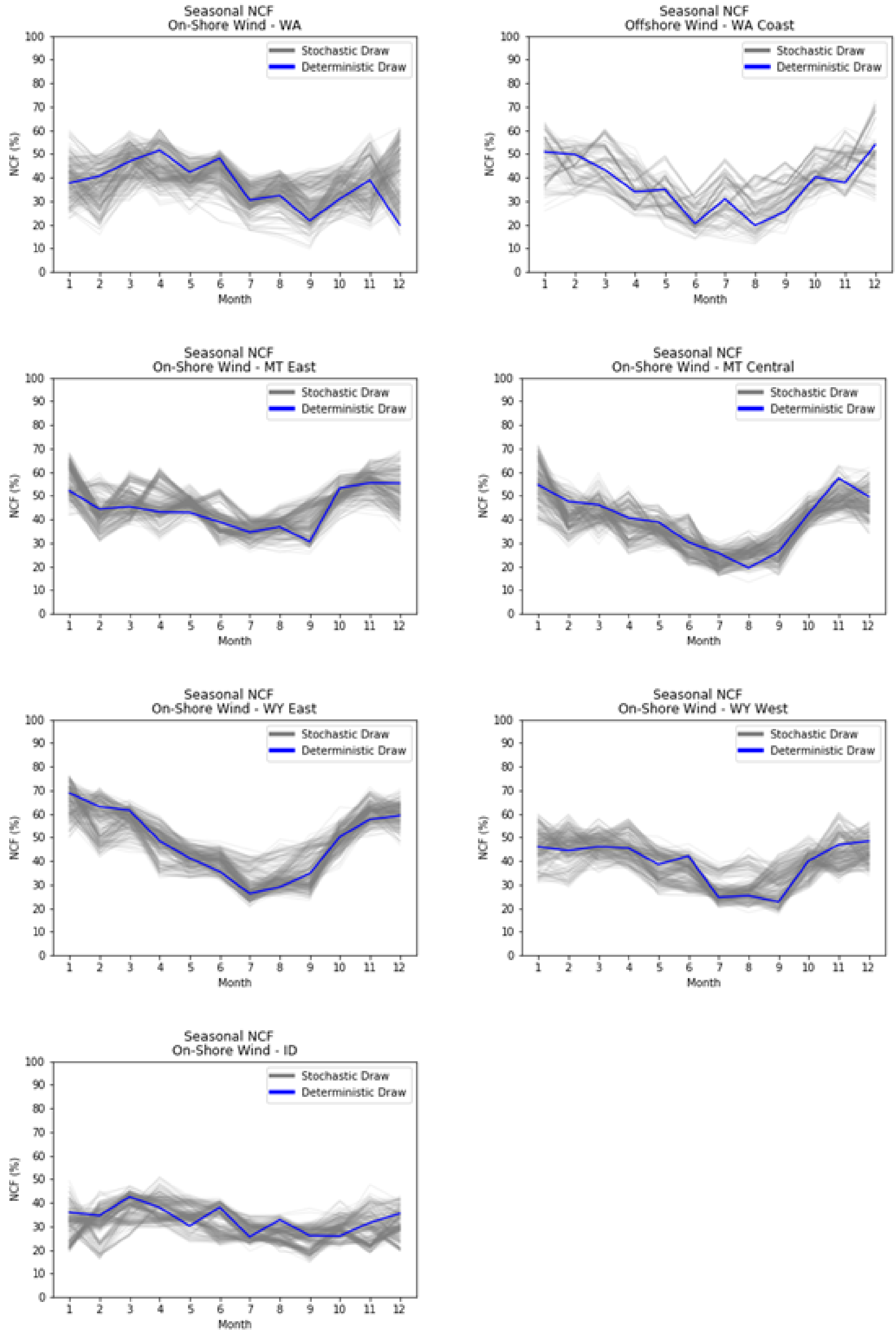
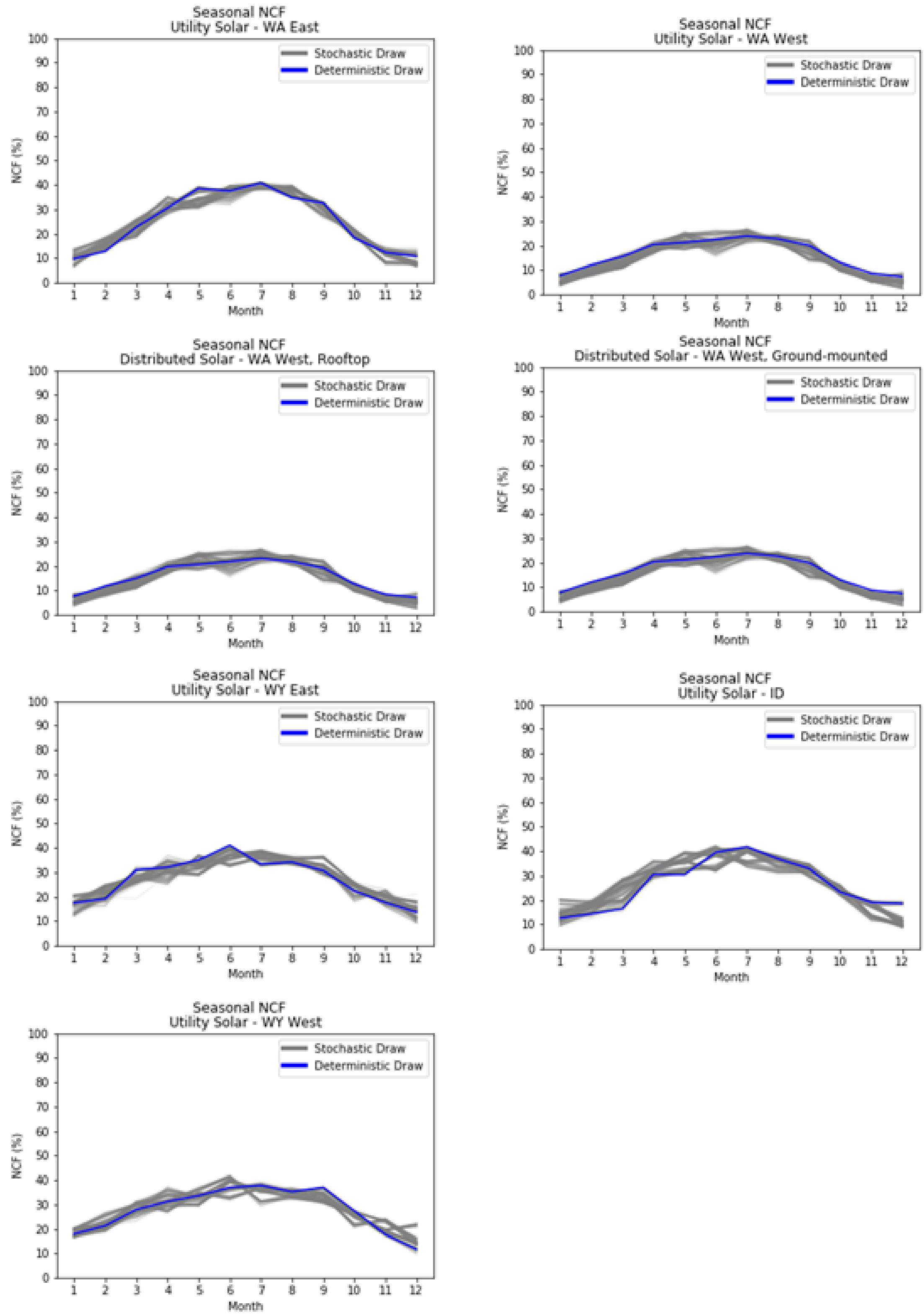


Figure G-30: The Seasonal Capacity Factors of All Generic Utility-scale Solar Resources



FORCED OUTAGE RATES. In AURORA, each thermal plant is assigned a forced outage rate. This value represents the percentage of hours in a year where the thermal plant is unable to produce power due to unforeseen outages and equipment failure. This value does not include scheduled maintenance. In the stochastic modeling process the forced outage rate is used to randomly disable thermal generating plants, subject to the minimum down time and other maintenance characteristics of the resource. Over the course of a stochastic iteration, the total time of the forced outage events will converge on the forced outage rate. The Frequency Duration 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 completely out of service.

STOCHASTIC PORTFOLIO RESULTS. PSE tested the Mid Scenario portfolio, Sensitivity W Balanced Portfolio with Alternative Fuel for Peakers, Sensitivity WX Balanced Portfolio with Alternative Fuel for Peakers and Reduced Firm Market Access at Peak, and Sensitivity Z No DSR portfolio for the stochastic portfolio analysis. Stochastic results are discussed in Chapter 8, Electric Analysis and the data is available in Appendix H, Electric Analysis Inputs and Results.

Challenges and Next Steps

PSE is very conscious of model limitations and computer run times. We have discussed the idea of the varying hydro, wind and solar for each year in the planning horizon, but we need to ask ourselves, what is the benefit? What are we trying to model? PSE is trying to model the robustness of the portfolio. If we commit to a certain set of builds and the future is different than expected, will there be enough resources to meet needs? Total model run time for PSE's current stochastic electric price forecast model takes about 4 hours per draw to run the simulation, so that is 20,420 hours or 14 days to do the current simulations. By dividing the computer cores to run 4 parallel simulations, it takes about 4 days to complete 80 draws of price forecasts while not changing the hydro and wind draws for each year. PSE's current stochastic portfolio model takes about 1 hour per draw to run the simulation, so that is 310 hours or 12.9 days to do the current simulations. By dividing the computer cores and sharing out among 6 machines, it takes about 2 days to complete one portfolio simulation by keeping the portfolio static and not changing the hydro, wind and solar draws for each year. Once the machine is in use, PSE staff is unable to utilize the machine for other work processes.

Another question that came up was why the resource builds are fixed and do not vary by simulation. The Long Term Capacity Expansion Model which determines new resource builds and retirements takes from 18 to 24 hours to run one complete simulation for a portfolio. If PSE were to run the LTCE for each stochastic draw, then that would take 18 hours * 310 draws = 5,580 hours / 24 = 232 days to complete a portfolio optimization for all 310 possible futures. PSE is working with Energy Exemplar on model run times. At most, we might be able to decrease run times by half. This is why PSE does the sensitivity model, to isolate out several of the variables to see how that would affect portfolio builds and costs.

PSE acknowledges that inputs which vary year to year as well as simulation to simulation would provide a more nuanced analysis. PSE will explore opportunities to incorporate these changes into future IRP cycles. For the 2021 IRP, PSE suggests that static inputs as modeled still provide meaningful results and adequately bracket the upper and lower bounds of expected results as well as provide insight into various possible futures.

PLEXOS Flexibility Analysis Model

PLEXOS is used to estimate the impact of selected generic resources on system dispatch cost at a sub-hourly timeframe. PLEXOS is a sophisticated software platform that uses mathematical optimization combined with advanced handling and visualization to provide a high-performance, robust simulation system for electric power, water and gas. It is an hourly and sub-hourly chronological production simulation model which utilizes mixed-integer programming (MIP) to simulate electric power market, and to co-optimize energy and ancillary service provisions. The model first performs unit commitment and economic dispatch at a day-ahead level, and then redispatches these resources in real-time to match changes in supply and demand on a 15-minute basis.

For the sub-hourly cost analysis using PLEXOS, PSE created a current portfolio case based on PSE's existing resources, then tested each resource in the portfolio and calculated the cost difference in the real-time re-dispatch from the current portfolio case. The purpose of the flexibility analysis is to explore the sub-hourly flexibility needs of the portfolio and determine how new resources can contribute to those needs. Flexibility benefit = day-ahead (DA) dispatch costs – Intra-hour (IH or "real-time") dispatch costs. The flexibility benefit is then calculated as the total cost ($) / nameplate (MW) of resources as a fixed benefit per year ($/kw-year), and then added back to the resource in the capacity expansion model for making resource decisions.

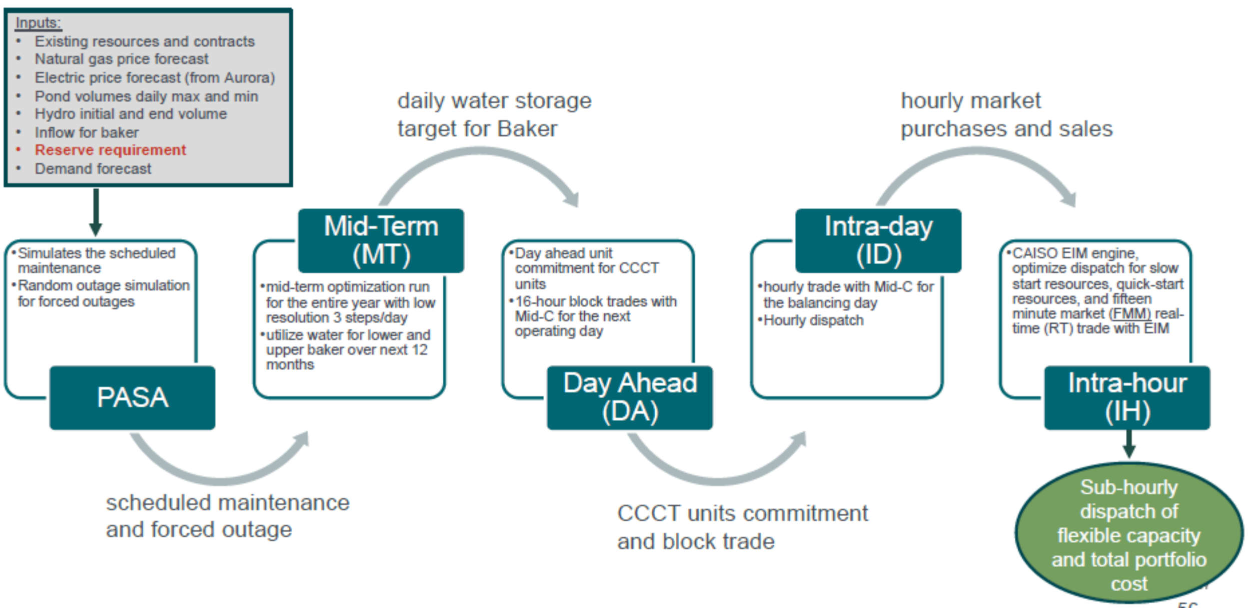
PLEXOS Simulation Phases

PSE utilized a five-stage simulation approach in PLEXOS. Each stage runs separately. The detailed inputs and outputs can be found in the Appendix H.

1. First, the Long-Term Projected Assessment of System Adequacy (PASA) stage incorporates scheduled maintenance and random outages. It simulates the availability of the generation units with the given forced outage rates and the scheduled maintenance information for the entire planning period, e.g., 25 years.
2. Then the Mid-Term stage runs a low-resolution version of the model that optimizes water usage at the Baker River Hydroelectric Project for the entire year with low resolution 3 steps/day, i.e., study year 2025.
3. The Day-Ahead stage then commits CCCT units on the hourly basis while also performing block trades with the Mid-C market on the basis of peak hour blocks and off peak hour blocks.
4. Next, the Intra-Day stage performs the hourly dispatch in the form of linear programming with the fixed commitments from the DA stage and trades on an hourly basis with the Mid-C market.

5. Finally, the Intra-Hour stage optimizes dispatch on the fifteen-minute. The PSE PLEXOS model also has the CAISO EIM engine. It can optimize dispatch for slow start resources, quick-start resources, and fifteen minute market (FMM) real-time (RT) trade with EIM. A full view of the PLEXOS modeling process can be viewed in Figure G-31.

Figure G-31: PLEXOS Simulation Phases



PLEXOS Model Inputs

CONTINGENCY RESERVES. Bal-002-WECC-1 requires balancing authorities to carry reserves for every hour: 3% of online generating resources and 3% of load to meet contingency obligations.

BALANCING RESERVES. 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 kind of short-term, forced-outage reliability benefit as contingency reserves, which are triggered only when certain criteria are met. Balancing reserves are resources that have the ability to ramp up and down instantaneously as loads and resources fluctuate each hour.

The balancing reserve requirements were assessed by E3 for two study years, using the CAISO flex ramp test. 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 7.

NATURAL GAS PRICES. For natural gas prices, PSE uses a combination of forward market prices and fundamental forecasts acquired in Spring 2020 from Wood Mackenzie. The natural gas price forecast is an input into the AURORA Electric Price Modeling and AURORA Portfolio Model. The natural gas price inputs as described in Chapter 5.

ELECTRIC PRICES. The electric price forecast was developed using AURORA (described above) and input into Plexos. This was used for the Mid-C day ahead and hourly trades. Using the Step Method, Plexos extrapolated the 15-minute electric prices for the EIM market.

DEMAND FORECAST. PSE's demand forecast described in chapter 6 is an input into Plexos using the monthly energy need (MWh) and peak need (MW). Using the Boundary Interpolate method, Plexos extrapolated the hourly and 15-minute loads using the 2019 historical load shapes.

Flexibility Benefit

To estimate the flexibility benefit of incremental resources, PLEXOS first runs the base case, which contains only PSE's current resource portfolio. Then, PLEXOS is run again with the addition of one new generic resource. The sub-hourly production cost result of the case with the base portfolio is then compared to the production cost of the case with the additional resource.

Any cost reduction to the portfolio is assumed to be attributed to the new resources. PSE tested each generic and thermal resource identified in the IRP and incorporated the flexibility benefit to the cost in the portfolio analysis. To avoid double counting, only cost reductions provided at the IH stage (incremental to DA stage cost savings) are added to the portfolio analysis.

The flexibility benefit calculation process is summarized below.

1. System cost savings between the two cases in the day-ahead stage
2. System cost savings between the two cases in the intra-hour stage
3. System cost savings between the day-ahead delta from (1) and intra-hour delta from (2)
4. Then the System cost savings from (3) divided by the nameplate of the resource to calculate them on a $/kW-year basis. This is called the flex benefit and a description with results is in Chapter 5.

The results for the flexibility benefit and flex violations are included in Appendix H.

2. AVOIDED COSTS

IRP Avoided Costs

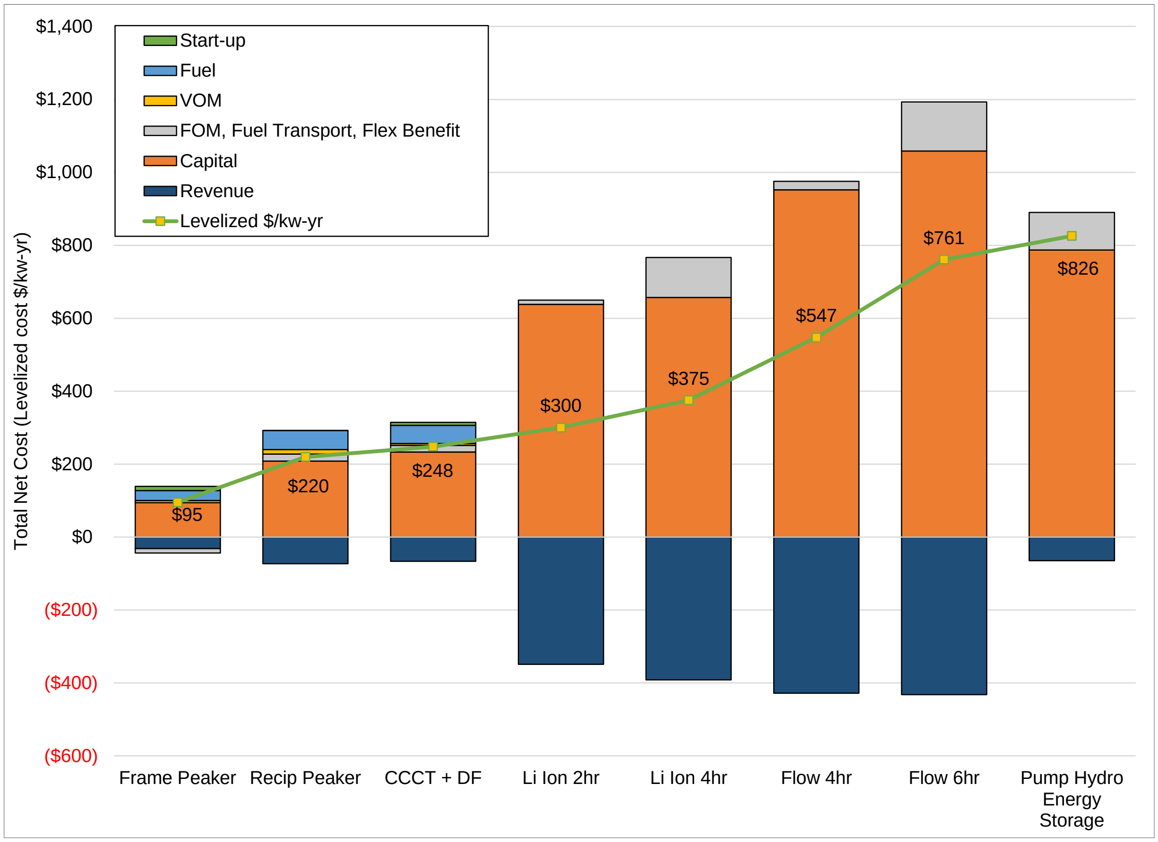
Consistent with WAC 480-100-620(13), the estimated avoided costs in this section provide only general information about the costs of new power supplies and is only used for planning purposes. This section includes estimated capacity costs consistent with the resource plan forecast, transmission and distribution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

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

The indicative avoided capacity resource costs can be found in Appendix H. The costs are “net” capacity costs, meaning that the energy or other resource values have been deducted, using the Mid Scenario results. For example, frame peakers can dispatch into 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 kinds of 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 the effective load carrying capability (ELCC) analysis in this IRP. The ELCC for a firm, dispatchable resource would be 100 percent, but different kinds of intermittent resources would have different peak capacity contributions. The capacity contributions used here are consistent with those described in Chapter 7. Figure G-32 below is the levelized cost of capacity (LCOC) compared across different resources. The LOC is discussed in Chapter 8.

Figure G-32: Net Cost of Capacity in the Mid Scenario Portfolio Model



PSE's preferred portfolio for the 2021 IRP is documented in Chapter 3 with explanations of why different resources are added to the portfolio. The first resource added to the portfolio for capacity needs is the frame peaker in 2026 at a cost of $95/kw-yr. Even though other resources are added to the portfolio in earlier years, they are added for other reasons, for example distributed energy resources (DERs) such as batteries. DERs make lower peak capacity contributions and have higher costs, but they play an important role in balancing utility-scale renewable investments and transmission constraints while also meeting local distribution system needs and improving customer benefits. Which is why the frame peaker is used as the avoided cost of capacity.

TRANSMISSION AND DISTRIBUTION (T&D). A transmission and distribution deferral value of $15.15/kW-year was included as a negative cost item in the resource value for distributed battery energy storage, demand response and Demand-Side resources. This is an internal PSE calculated number based on current project costs.

GHG EMISSIONS. PSE relies on market purchases to help balance the portfolio, so the avoided emissions from added new non-emitting resources is from unspecified market purchases.

Section 7 of E2SB5116, paragraph 2 states to use 0.437 metric tons CO_2/MWh for unspecified market purchases. The emission cost is calculated as follows:

SCGHG ($/ton) * 0.437 (tons/MWh) = emission cost ($/MWh)

Figure G-33 below is the emission cost adder in dollars per MWh.

Figure G-33: SCGHG Cost Adder

(Nominal $/MWh)	
2022	36.10
2023	37.58
2024	39.11
2025	41.30
2026	42.96
2027	44.67
2028	46.44
2029	48.27
2030	50.17
2031	52.12
2032	54.15
2033	56.24
2034	58.41
2035	60.65
2036	62.96
2037	66.17
2038	68.66
2039	71.23
2040	73.89
2041	76.64
2042	79.48
2043	82.42
2044	85.45
2045	88.58

ENERGY. PSE relies on market purchases to help balance the portfolio, so the avoided energy is market purchases. Therefore, PSE's avoided energy costs are clearly avoiding Mid-C market purchases. Peakers are capable of generating energy, so they temper PSE's exposure to market prices, at least when market heat rates (the spread between natural gas prices and power prices) increase. This means using a forecast of market prices could tend to overstate avoided energy costs during some hours – but only for short periods.

Figure G-34 shows the forecast of average monthly power prices and forecast of average annual market power prices at Mid-C for the Mid Scenario. This is the set of avoided energy costs PSE suggests would be the most informative for potential suppliers. The electric price also included in Appendix H.

Schedule of Estimated Avoided Costs for PURPA

This schedule of estimated avoided cost, as prescribed in WAC 480-106-040 identifies the estimated avoided costs for qualifying facilities and does 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 the following two tables:

Figure G-34: 2022-2041 Avoided Energy Costs based on the Company's forecast of market prices for the Mid-C Market in PSE's 2021 Integrated Resource filed April 1st, 2021, pursuant to WAC 480-106-040(a).

Figure G-35: 2021-2041 incorporates the avoided capacity costs as estimated in the Company's 2021 Integrated Resource Plan. The 2021 IRP was filed on April 1, 2021. Pursuant to WAC 480-106-040(b)(ii), the 2021 IRP first capacity addition is 2026, so results for 2022-2025 are replaced with the "projected fixed costs of a simple-cycle combustion turbine."

Figure 34: 2021 IRP Forecast of Mid-C Market Prices

(Nominal $/MWh)													
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg.
2022	26.56	27.65	20.55	15.10	9.49	11.31	21.01	22.88	24.31	23.59	24.69	27.53	21.19
2023	25.24	26.50	19.77	14.79	9.70	10.29	20.13	21.93	23.68	23.11	24.42	27.09	20.53
2024	24.49	25.82	18.79	13.88	7.17	9.23	18.46	22.35	24.00	22.97	24.39	26.06	19.79
2025	24.49	25.82	18.97	12.83	7.53	9.73	18.21	22.47	24.22	22.79	23.80	26.50	19.75
2026	24.38	26.73	18.20	13.87	7.99	9.55	18.67	22.57	24.01	23.09	23.99	26.99	19.97
2027	28.08	28.91	19.71	15.44	9.14	10.75	22.01	26.84	28.62	28.87	29.00	31.20	23.19
2028	28.71	29.47	19.64	16.52	9.08	11.20	23.79	28.14	32.15	31.02	30.01	33.37	24.42
2029	29.33	31.29	19.63	20.07	8.87	11.50	23.61	30.20	35.24	32.07	28.96	34.85	25.44
2030	29.05	30.29	18.28	18.75	8.06	10.96	22.71	29.93	34.66	32.94	30.73	34.61	25.05
2031	28.42	30.42	18.22	18.19	8.55	11.12	22.13	29.98	34.53	32.65	29.03	34.49	24.78
2032	28.24	29.21	18.31	19.43	10.21	10.67	23.05	29.05	33.67	34.86	32.28	35.65	25.38
2033	29.08	31.54	19.17	19.67	9.61	11.64	24.84	29.95	34.57	37.49	36.03	37.07	26.69
2034	29.79	32.26	19.17	19.69	10.51	12.34	27.12	30.25	36.25	37.68	35.17	38.81	27.40
2035	31.00	35.33	19.95	22.93	11.60	12.60	27.03	32.04	37.97	36.64	32.09	40.27	28.25
2036	31.90	35.40	20.49	21.57	11.51	13.52	29.25	34.32	39.07	38.76	38.04	42.85	29.71
2037	32.89	35.55	19.90	20.06	11.58	12.92	30.46	34.47	38.51	38.58	35.59	42.87	29.43
2038	33.05	34.31	19.61	20.59	12.34	12.73	30.02	34.49	38.54	38.11	34.60	43.72	29.33
2039	31.29	33.46	18.20	19.01	10.72	12.48	30.87	34.28	40.25	38.63	36.81	43.64	29.12
2040	31.22	33.69	17.21	18.62	10.00	12.67	30.73	33.44	41.90	38.88	37.62	46.67	29.38
2041	32.16	35.50	18.23	21.07	10.60	12.79	29.37	38.67	45.79	37.02	35.39	48.41	30.39

Figure 35: 2021 IRP Forecast of Mid-C Market Prices

(Nominal $/kw-yr)			
	Baseload Resource	**Wind Resource**	**Solar Resource**
2022	$ 95.27	$ 16.96	$ 3.81
2023	$ 95.27	$ 16.96	$ 3.81
2024	$ 95.27	$ 16.96	$ 3.81
2025	$ 95.27	$ 16.96	$ 3.81
2026	$ 95.27	$ 16.96	$ 3.81
2027	$ 95.27	$ 16.96	$ 3.81
2028	$ 95.27	$ 16.96	$ 3.81
2029	$ 95.27	$ 16.96	$ 3.81
2030	$ 95.27	$ 16.96	$ 3.81
2031	$ 95.27	$ 14.67	$ 3.43
2032	$ 95.27	$ 14.67	$ 3.43
2033	$ 95.27	$ 14.67	$ 3.43
2034	$ 95.27	$ 14.67	$ 3.43
2035	$ 95.27	$ 14.67	$ 3.43
2036	$ 95.27	$ 14.67	$ 3.43
2037	$ 95.27	$ 14.67	$ 3.43
2038	$ 95.27	$ 14.67	$ 3.43
2039	$ 95.27	$ 14.67	$ 3.43
2040	$ 95.27	$ 14.67	$ 3.43
2041	$ 95.27	$ 14.67	$ 3.43
2042	$ 95.27	$ 14.67	$ 3.43
2043	$ 95.27	$ 14.67	$ 3.43
2044	$ 95.27	$ 14.67	$ 3.43
2045	$ 95.27	$ 14.67	$ 3.43