

Planning Standards and Resource Planning

2018 IRP Update - Supplemental Technical Working Group

2018 IRP Supplemental Technical Working Group

June 3, 2021



Agenda

Introduction

Planning Standards

Peak-Day Planning Standard and Gas
Supply Planning

Firm Sales Peak Day Load Forecast
Modeling Process

Daily System Load Model

Monte Carlo Simulation

Peak Day Load Forecast

Distribution System Planning and Peak
Hour Planning Standard



Take 2 Minutes for Safety: Insect Bites and Stings

Working outdoors comes with the risk of insect bites and stings. Most may only cause mild symptoms, but some can lead to severe allergic reactions. Prevention is always the first step.

○ Sting and Bite Prevention

- Inspect your work area for signs of bees, wasps, spiders, and other critters
- Keep work areas free of food/beverage, and avoid wearing fragrances
- Wear clothing that covers as much of the body as possible
- Remain calm, and avoid swatting (swatting can instigate stings)
- If severely allergic, carry an epinephrine autoinjector and or medical IDs



○ If Bitten or Stung

- Bee stingers should be removed as soon as possible using gauze or by scraping a fingernail over the area (do not squeeze or use tweezers)
- Seek immediate medical attention if bite/sting causes severe chest pain, nausea, sweating, swelling, loss of breath, and or slurred speech.
- Wash the site with soap and water
- Apply ice to reduce swelling

TWG Members and Stakeholders

Oregon Public Utility Commission Staff
(OPUC)

Washington Utilities and Transportation
Commission Staff (WUTC)

Washington Office of the Attorney General
(Public Counsel)

Oregon Citizen's Utility Board (CUB)

Alliance of Western Energy Consumers
(AWEC)

NW Energy Coalition (NWEC)

Northwest Gas Association (NWGA)

Energy Trust of Oregon

Utilities

Business Partners

Additional Participants

Planning Standards

OPUC Order No. 19-073

Staff Recommendation No. 5

“Prior to the 2020 IRP, Staff recommends NW Natural coordinate a TWG focused on the Company's method of implementing probabilistic methodology for the capacity planning standard and peak hour standard for distribution system planning. NWN should share the relevant modeling inputs, outputs, and workpapers with stakeholders at least one week in advance of the TWG.”

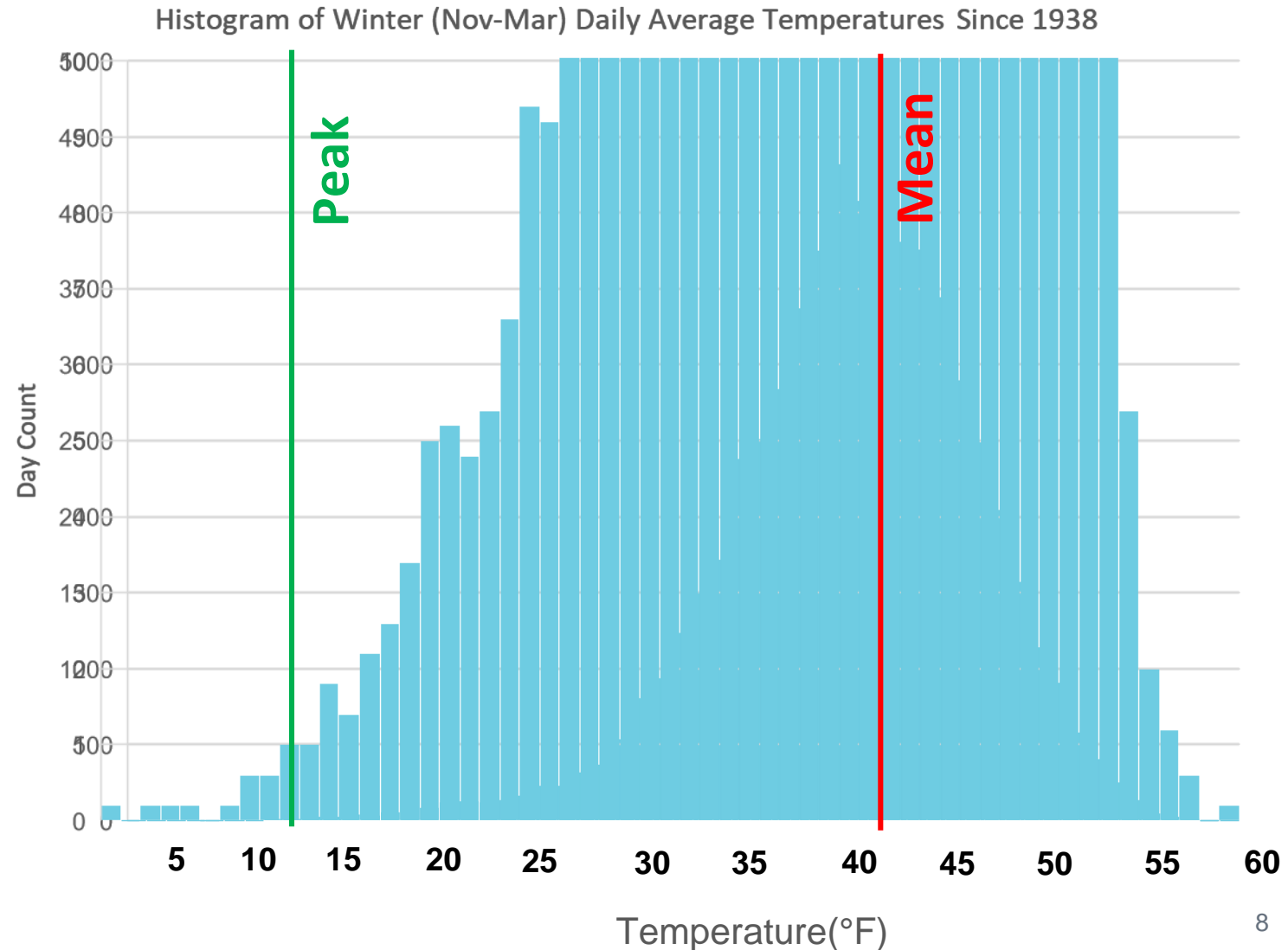
Goals of Planning Standards

- Planning standards set the threshold level of energy services demanded by customers by which the utility can safely, reliably, and affordably serve customers
- Planning standards balance safety and reliability with affordability
- Natural gas LDC planning standards are typically strict due to the high stakes and consequences of outages which would occur during cold events



Goals of Planning Standards

- NW Natural has historically planned for safe, reliable, and affordable system capacity resources and will continue to do so in the future.
- **IRP Guideline 11**
Natural gas utilities should analyze, on an integrated basis, gas supply, transportation, and storage, along with demand-side resources, to reliably meet peak, swing, and base-load system requirements.



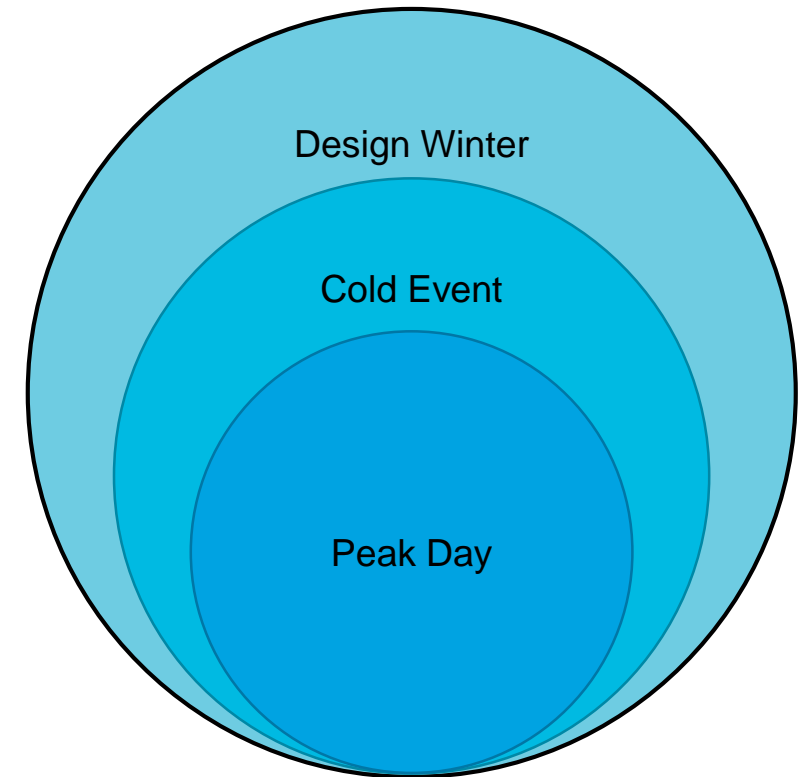
Two Categories of Capacity Planning Standards

1) Gas Supply Resource Planning Standards

- Design winter planning standard
- Cold event planning standard
- Peak-day planning standard

Gas supply resources are selected to meet the sales customer demand for **NW Natural's entire system**:

- Total sales demand in a year
- Seasonal changes in sales demand
- Maximum daily *firm* sales demand



Two Categories of Capacity Planning Standards

2) Distribution Resource Planning Standard

- Peak-hour planning standard

Distribution resources are selected to meet the sales and transportation customer demand for relevant areas of NW Natural's service territory:

- Total sales and transportation demand in a year
- Seasonal changes in sales and transportation demand
- Maximum hourly (instant) ***firm*** sales and ***firm*** transportation demand



Peak-Day Planning Standard and Gas Supply Planning

Firm Sales Peak Day Planning Standards Over Time

2014 IRP

- Highest expected firm sales demand day based on temperature only
- Actual temperature from February 3, 1989

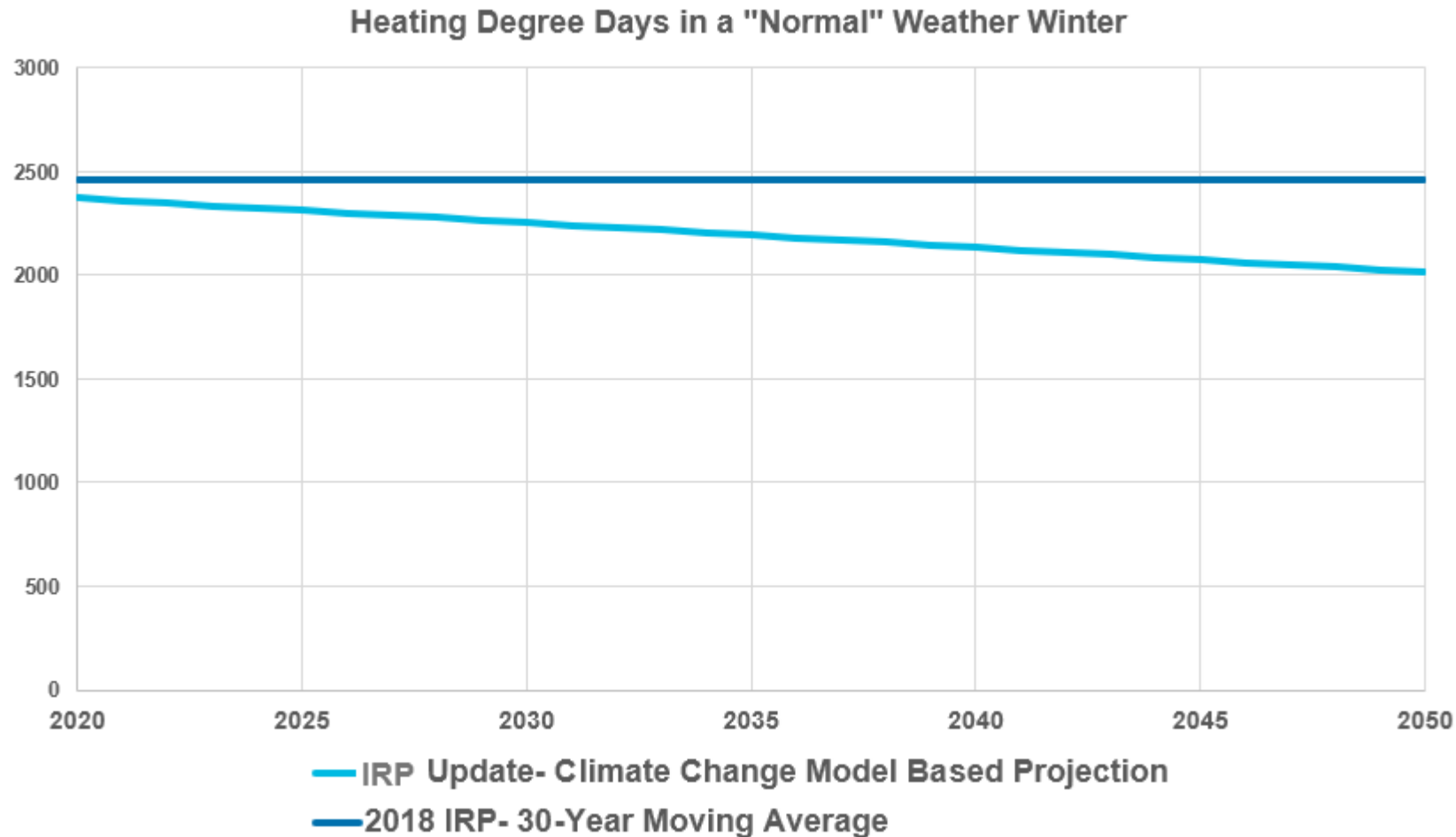
2016 IRP

- Highest expected firm sales demand day based on temperature and additional weather variables
- Actual weather from February 3, 1989

2018 IRP

- Plan supply capacity resources to serve the highest firm-sales-demand day going into each gas year with 99% certainty assuming all resources are available (i.e., no forced outages)
- Uses a Monte Carlo simulation of the highest demand day in a heating season based on historical data

NW Natural is Modeling Climate Change Trends into Expected Weather and Design Winter Weather Forecasting



- While there is no indication that cold events are becoming less severe, there is clear evidence heating seasons are getting milder
- Implementing a similar approach to the NWPCC, NW Natural now incorporates leading climate change models into weather forecasting
- Results in 3% reduction in HDDs in 2020 and 18% in 2050

Are Extreme Cold Snaps Likely to be More or Less Severe?



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Science

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Atmospher Sci & Global Chg Research Highlights

April 2015

Cold Snaps Linger Despite Climate Change

Extreme cold episodes will continue despite climate warming trends according to researchers' analysis of winter temperature distributions

Results: Keep a winter coat and mittens handy. A new climate analysis from scientists at Pacific Northwest National Laboratory and the University of Reading (UK) found that in spite of climate warming, cold air outbreaks, or CAOs, are projected to continue over North America though less frequently. In a geographic swath stretching from Alaska and southwestern Canada to the northwestern and mid-western United States, the top five coldest historical events may still happen. Indeed, as humans, ecosystems, and societal infrastructures adapt to an average warmer climate, these findings show continued future challenges in coping with extreme cold events.

"Our research isolated the changes of future cold air outbreaks to changes in the mean, the variance, and the skewness of daily surface air temperature" said Dr. Yang Gao, postdoctoral researcher and atmospheric scientist at PNNL. "Our analysis identified processes that will regulate future CAOs and climate factors that conspire to produce a distinct spatial pattern of CAO changes in North America."



The top five historical cold events may still happen across North America, despite climate change, according to research led by PNNL. Heavy snow and cold temperatures, like those pictured in New York this past winter, impact the economy, human health, and energy use. Scientists are working to understand the frequency and severity of these cold snaps in the future. [Enlarge Image.](#)

Additional Information

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Why Change to a Probabilistic Firm Sales Peak Day Planning Standard?

NW Natural identified two related issues with our previous peak day definition that needed to be addressed:

1) The firm sales peak day requirement could change dramatically if:

NW Natural experiences a more extreme weather event than any experienced in the last 30 years

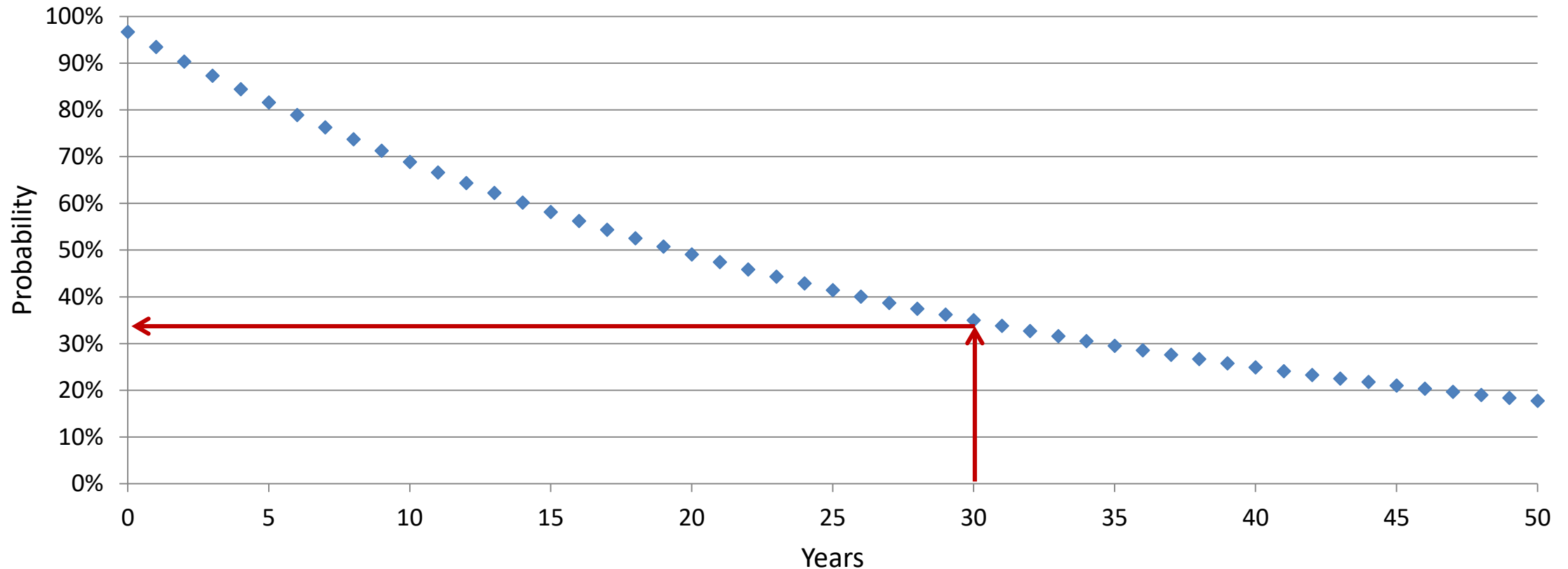
OR

30 years passes without experiencing a weather event as extreme

2) The highest demand day in the previous 30 years is not equivalent to a demand day that has a 1-in-30 probability of occurrence

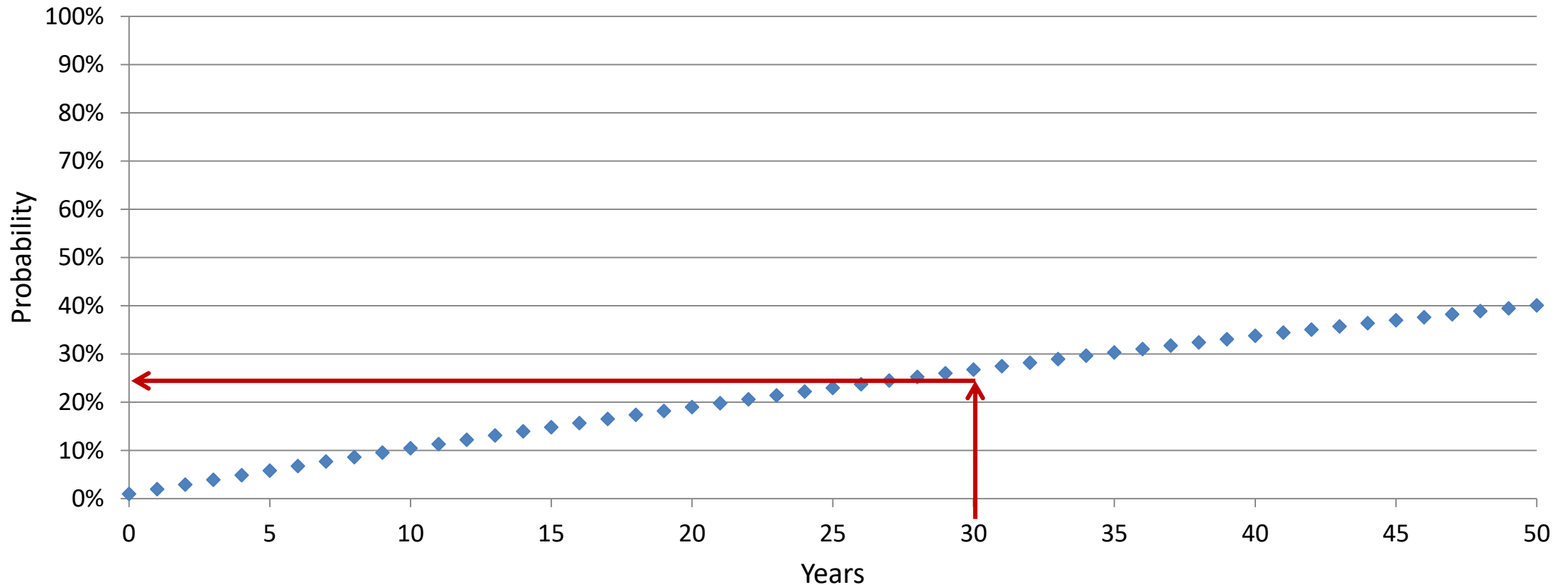
A true 1-in-30 event has a 3.333% (1/30) chance of occurring. On average, these events occur 30 years apart, but how often are they *more than* 30 years apart?

Probability of *at least* X years
between 1-in-30 events



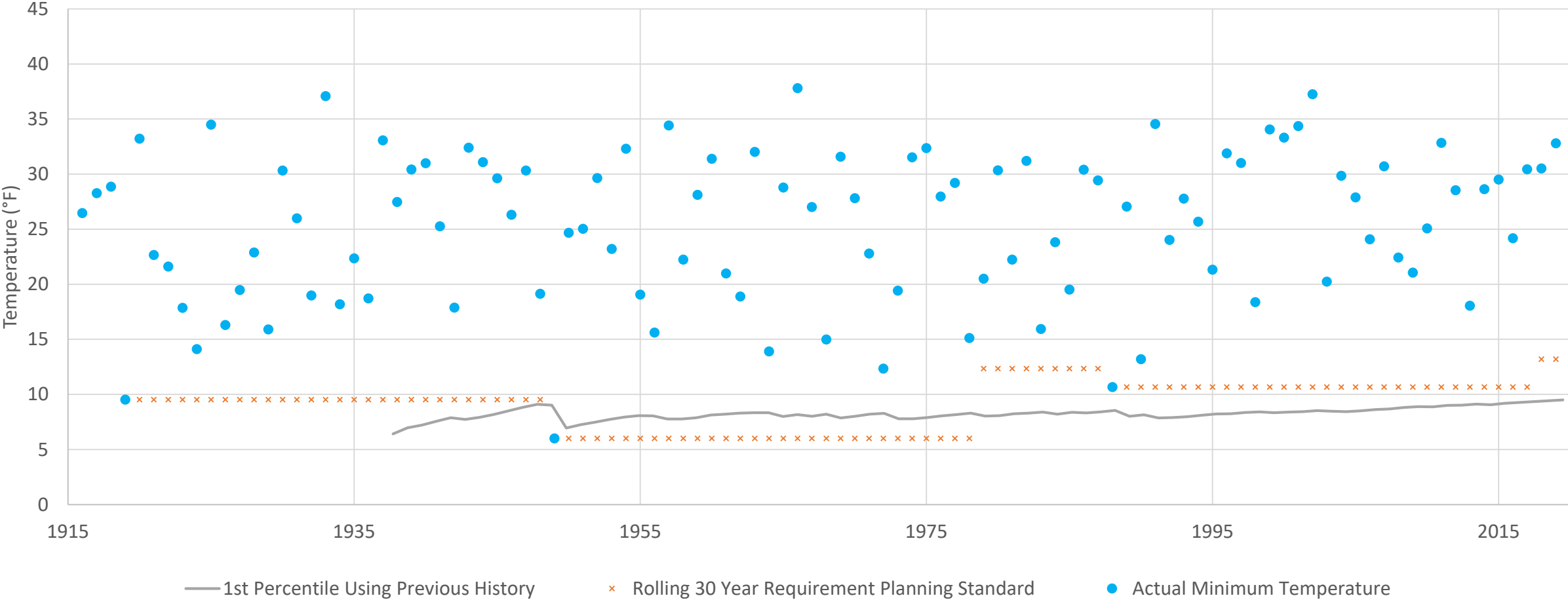
A true 1-in-100 event has a 1.0% (1/100) chance of occurring. On average, these events occur 100 years apart, but how often are they *less than* 30 years apart?

Probability of less than X years
between 1-in-100 events

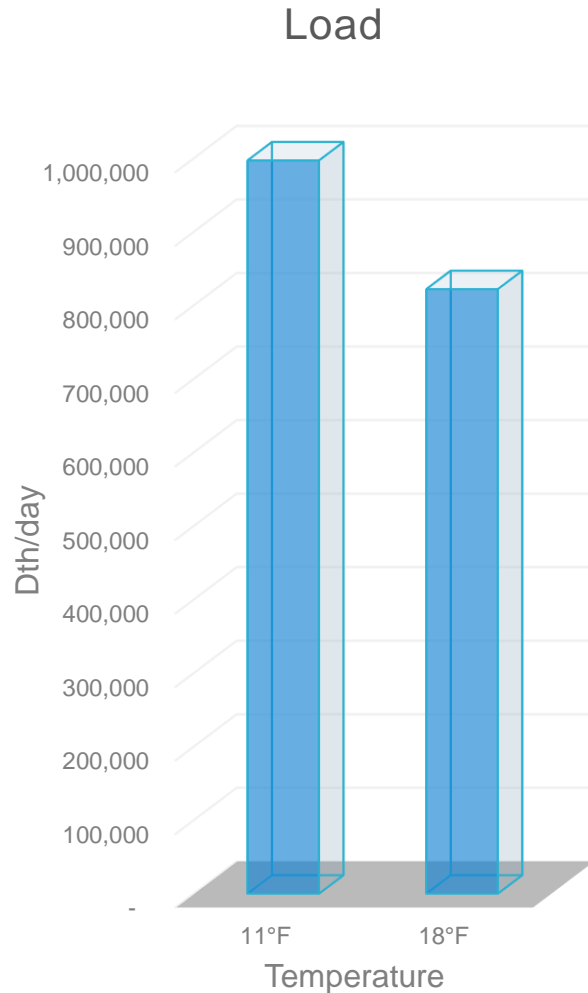


Stability of “COLDEST-IN-30” VS. ESTIMATED 1%

Coldest Daily Average System Weighted Temperature by Gas Year

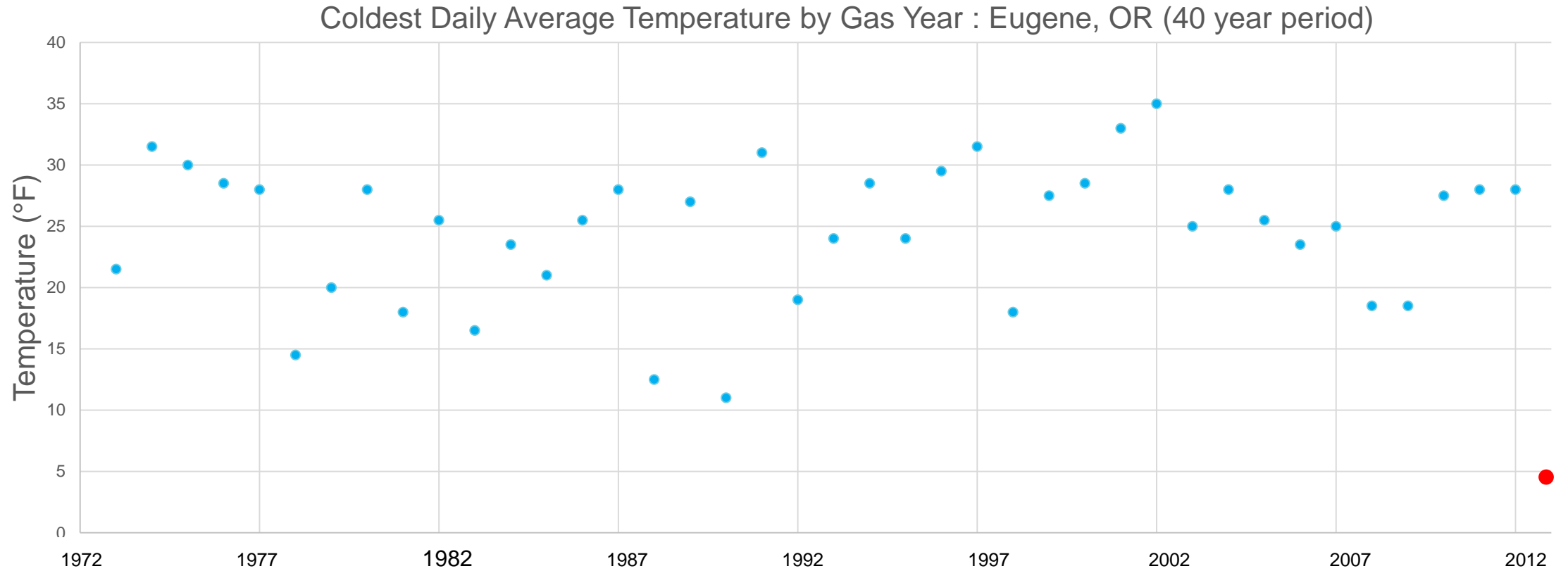


What Does This Mean for Customers...



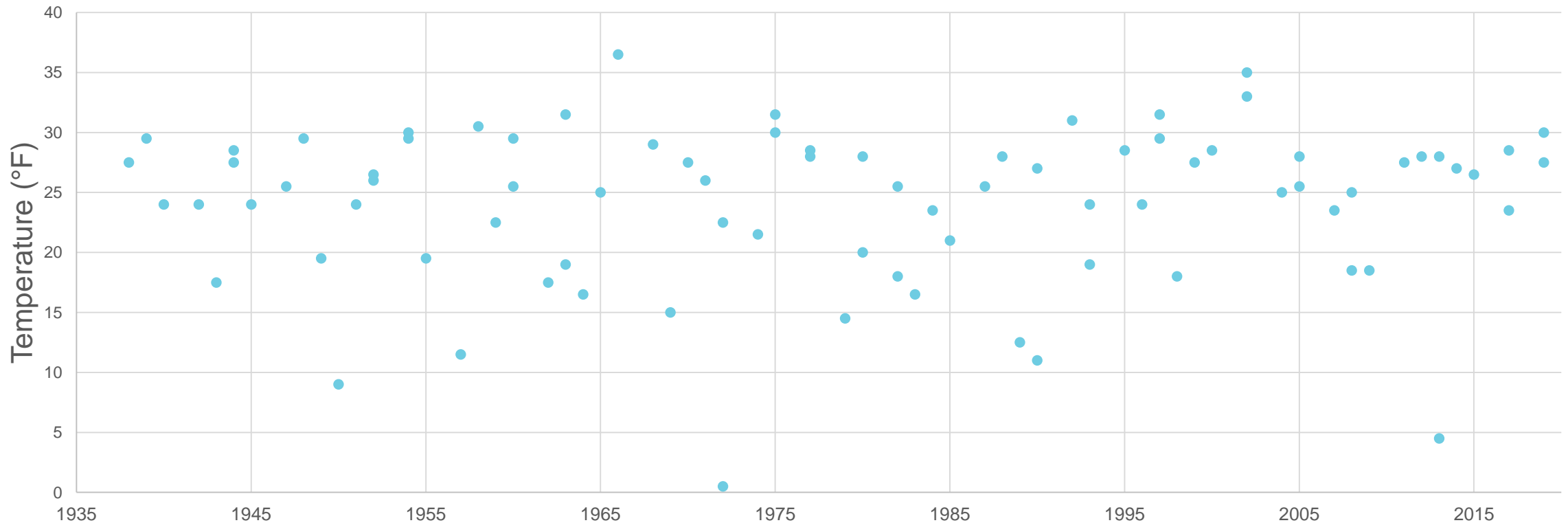
- The difference in firm sales system load between a 20°F day and a 11°F day is about 175,000 Dth consumed in a single day
- The typical residential customer uses roughly 1 Dth/day during a very cold day
- If we plan our resources for an 18°F day and a 11°F day occurs the shortage (without taking emergency measures) would be the equivalent of 25% of our residential customers experiencing an outage

Eugene

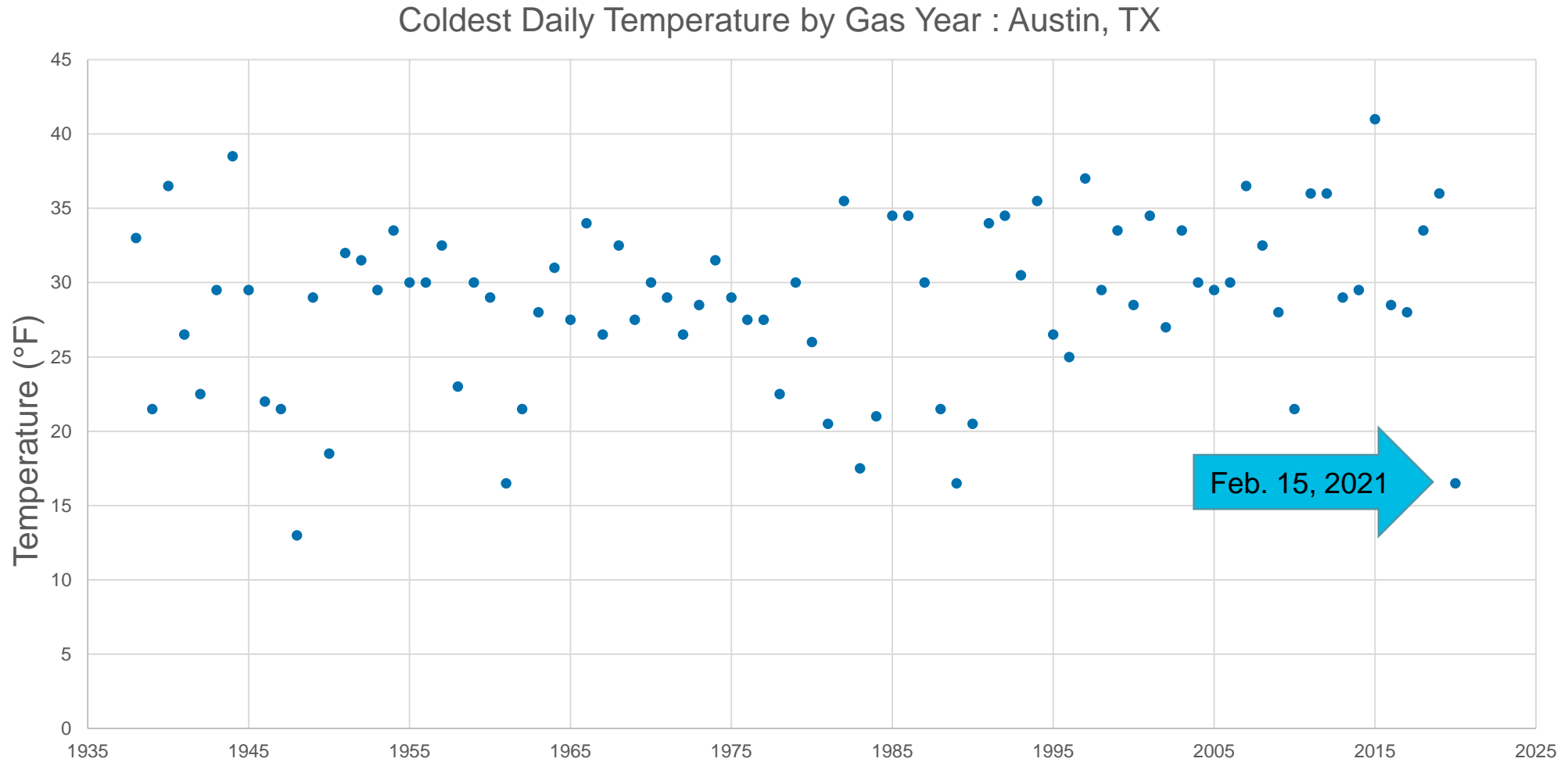


Eugene

Coldest Daily Average Temperature by Gas Year : Eugene, OR



Recent Events in Texas



High-Level Summary of Gas Supply Resource Planning Standards

Gas Supply Planning Standards

Design Winter

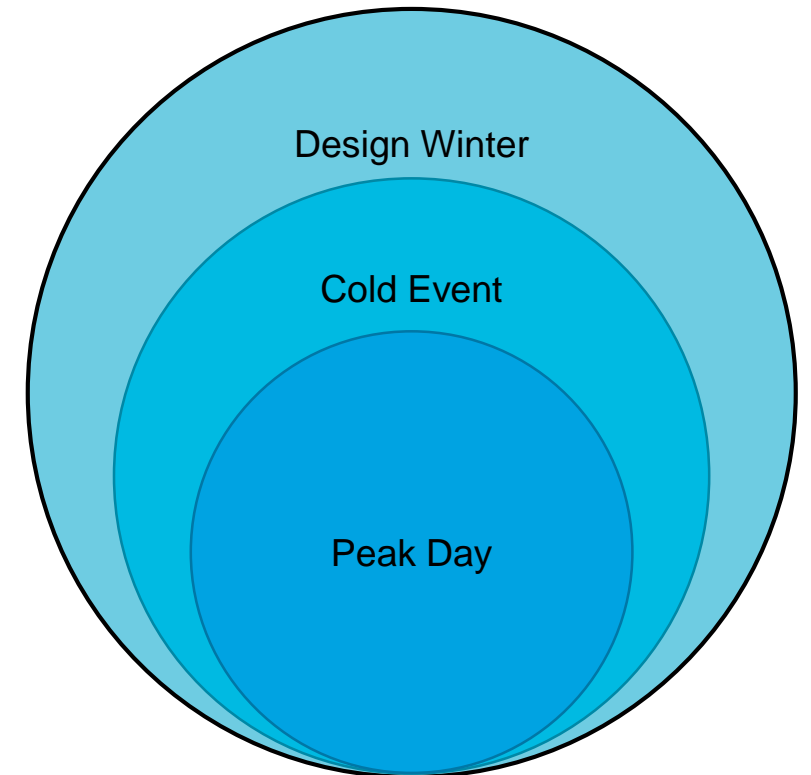
- Adjustment made to the represented weather (inclusive of climate change trends) based on a 90th percentile winter by cumulative winter HDDs (Nov-April) over the last 30 years

Cold Event

- 5-day cold event with regression modeling of the 2 days prior and 2 days after the coldest day of the year and applied to the peak day weather

Peak Day

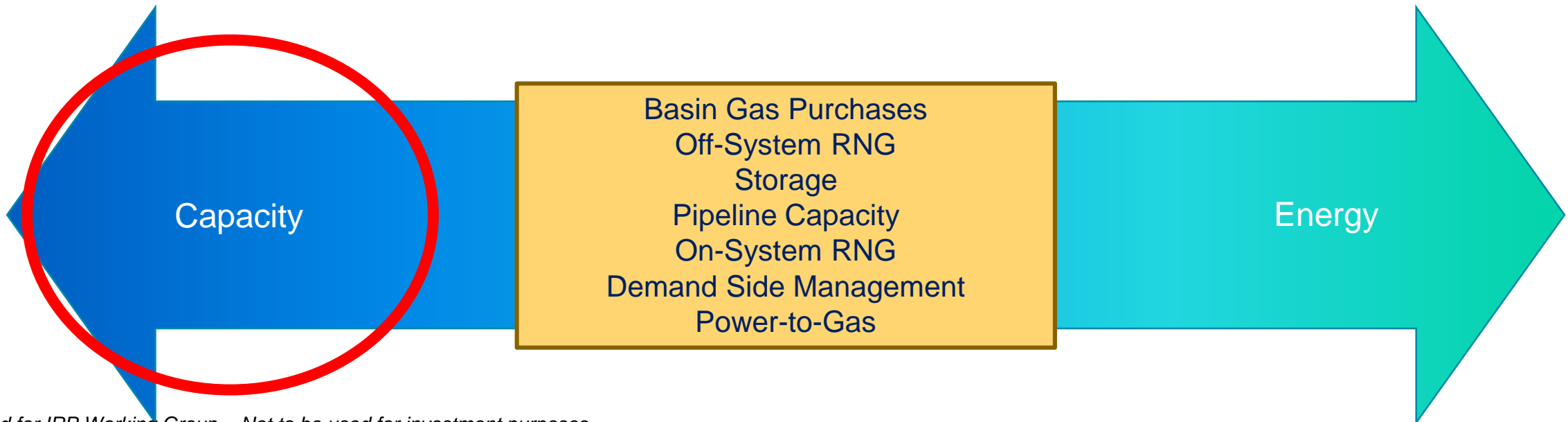
- Plan supply capacity resources to serve the highest firm sales demand day going into each gas year with 99% certainty assuming all resources are available (i.e. no forced outages)



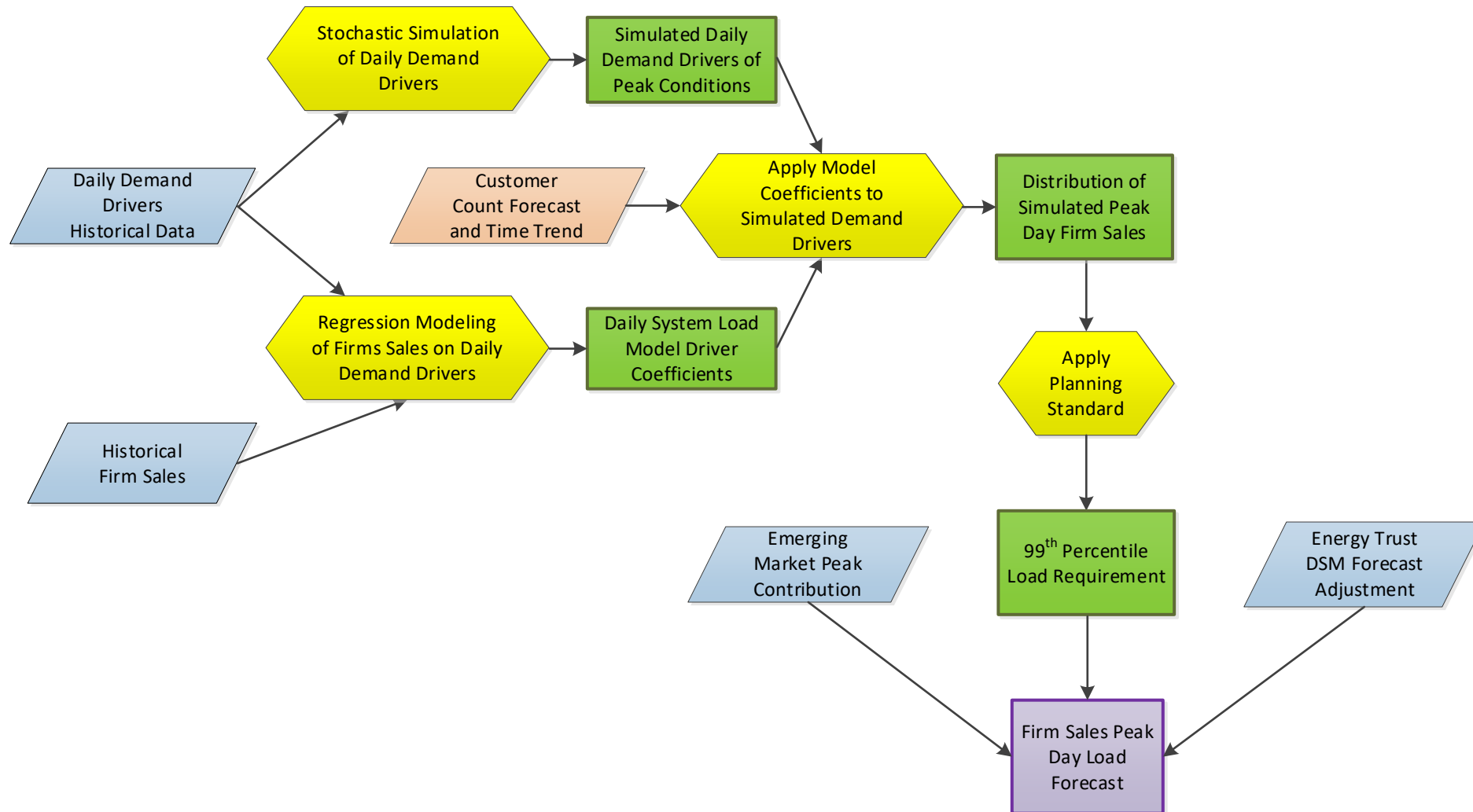
Firm Sales Peak-Day Load Forecast Modeling Process For Gas Supply Capacity Resources

Integrated Resource Planning

- NW Natural uses optimization software to select a portfolio of resources that minimizes total system costs in order to meet demand
- Finds the least cost balance of resources to meet both supply capacity requirements and energy requirements
- The firm sales Peak-Day Planning Standard primarily relates to the supply resource capacity requirements for gas resources

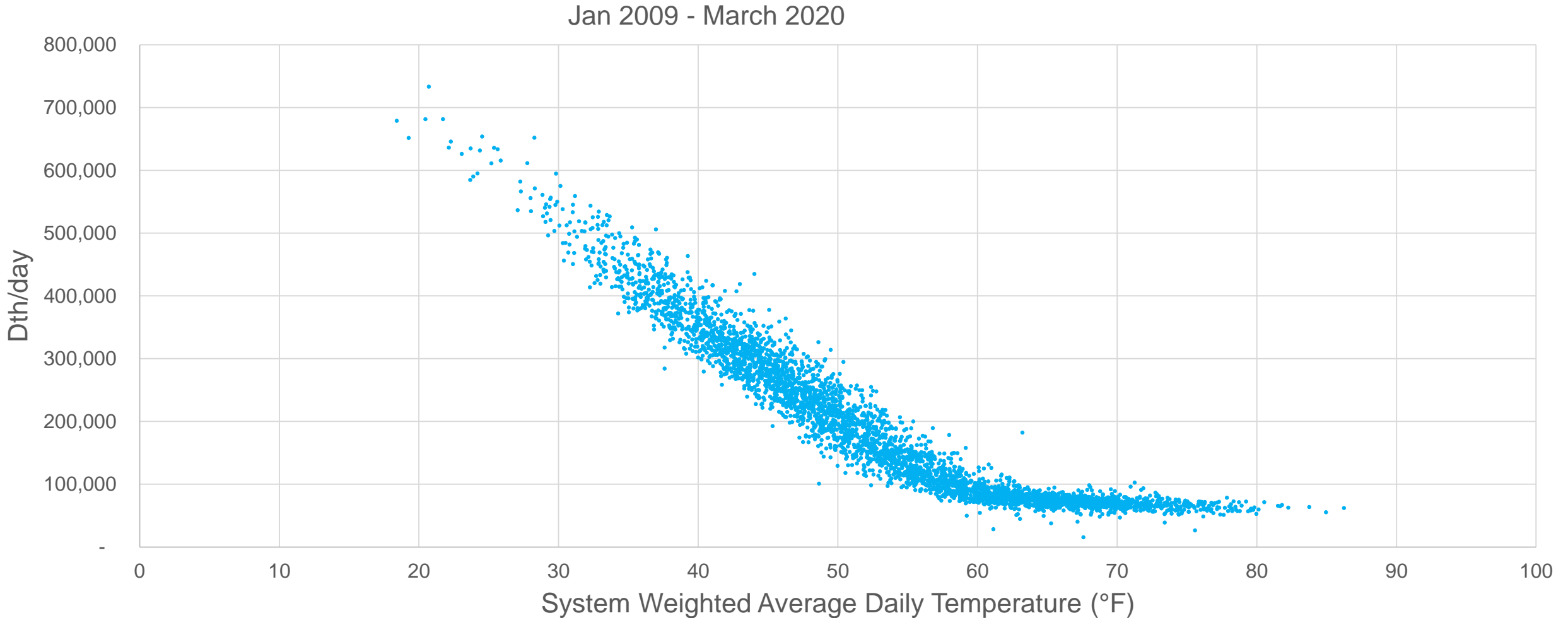


Firm Sales Peak Day Load Forecast Flow Chart



Daily System Load Model

Firm Sales Load and Temperature



Other Major Drivers



The Science of Wind Chill

NO WIND

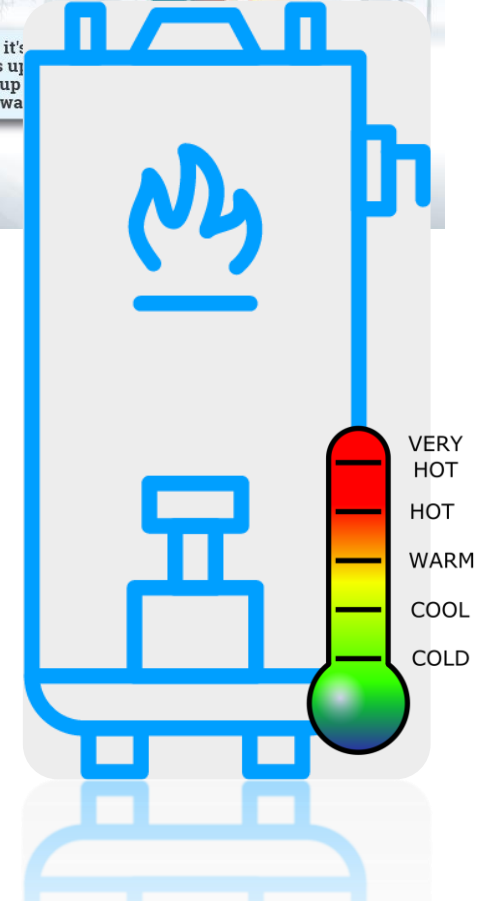
98.6°F
Average temperature of the human body

Under calm conditions, the body radiates heat, creating a layer of warmth between our skin and the cold surroundings.

WINDY

95°F
Hypothermia begins when our body temperature drops two to four degrees

But when it's windy, the air breaks up the warm layer. It speeds up the loss of heat away from the body.

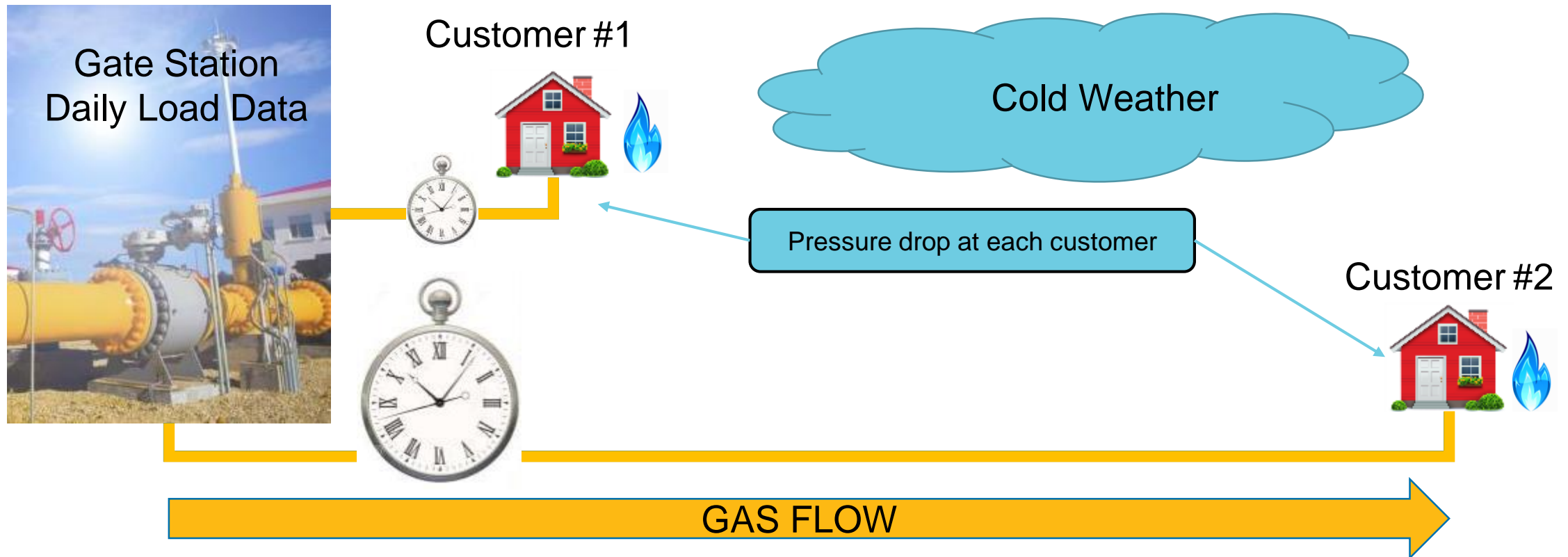
An infographic comparing a person in calm conditions (98.6°F) to a person in windy conditions (95°F). It includes a thermometer icon and a title "The Science of Wind Chill".

Summary of Driver Variables

Driver	Units	Relationship
Temperature	Hourly Average (°F)	(-)
Previous-Day Temperature	Hourly Average (°F)	(-)
Solar Radiation	Daily Sum (watts/m2)	(-)
Wind Speed	Hourly Average (mph)	(+)
Friday, Saturday, Sunday, Holiday	Indicator Variable [1,0]	(-)
Snow Depth	Daily Measure (inches)	(-)
Water Heater Inlet Temperature (Bull Run River Temperature)	Daily Measure (°F)	(-)
Customer Count	# of Customers	(+)
Time	Years after 2008	(-)

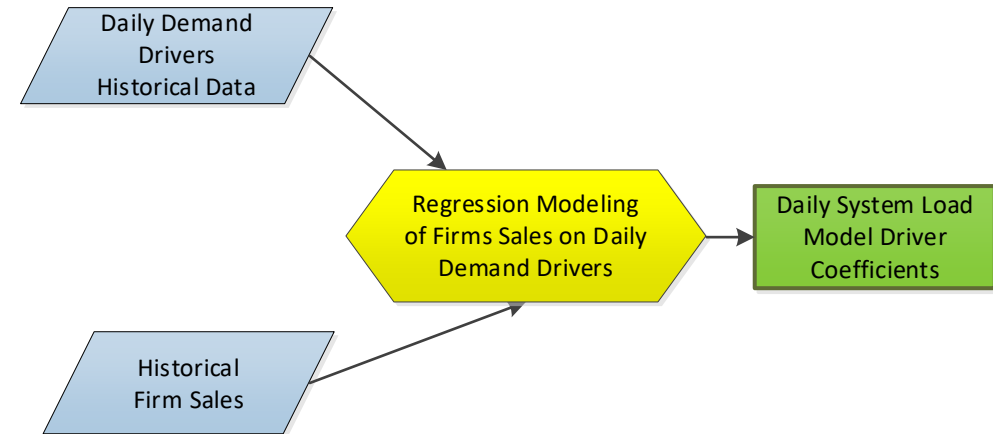
(-) = Inverse Relationship; (+) = Positive Relationship
 For example, as temperature ↑ gas demand ↓; as wind speed ↑ gas demand ↑

Load and Previous Day Temperature



Daily System Load Model

- The Daily System Load Model estimates daily system firm sales load as a function of daily demand drivers and interaction effects between those drivers and temperature
- For the peak-day forecast the model is trained on historical winter data (Nov-March) and days $\leq 58^{\circ}\text{F}$
- For the 2018 IRP Update #3, we used load data from January 2009-March 2020



OPUC Order No. 19-073

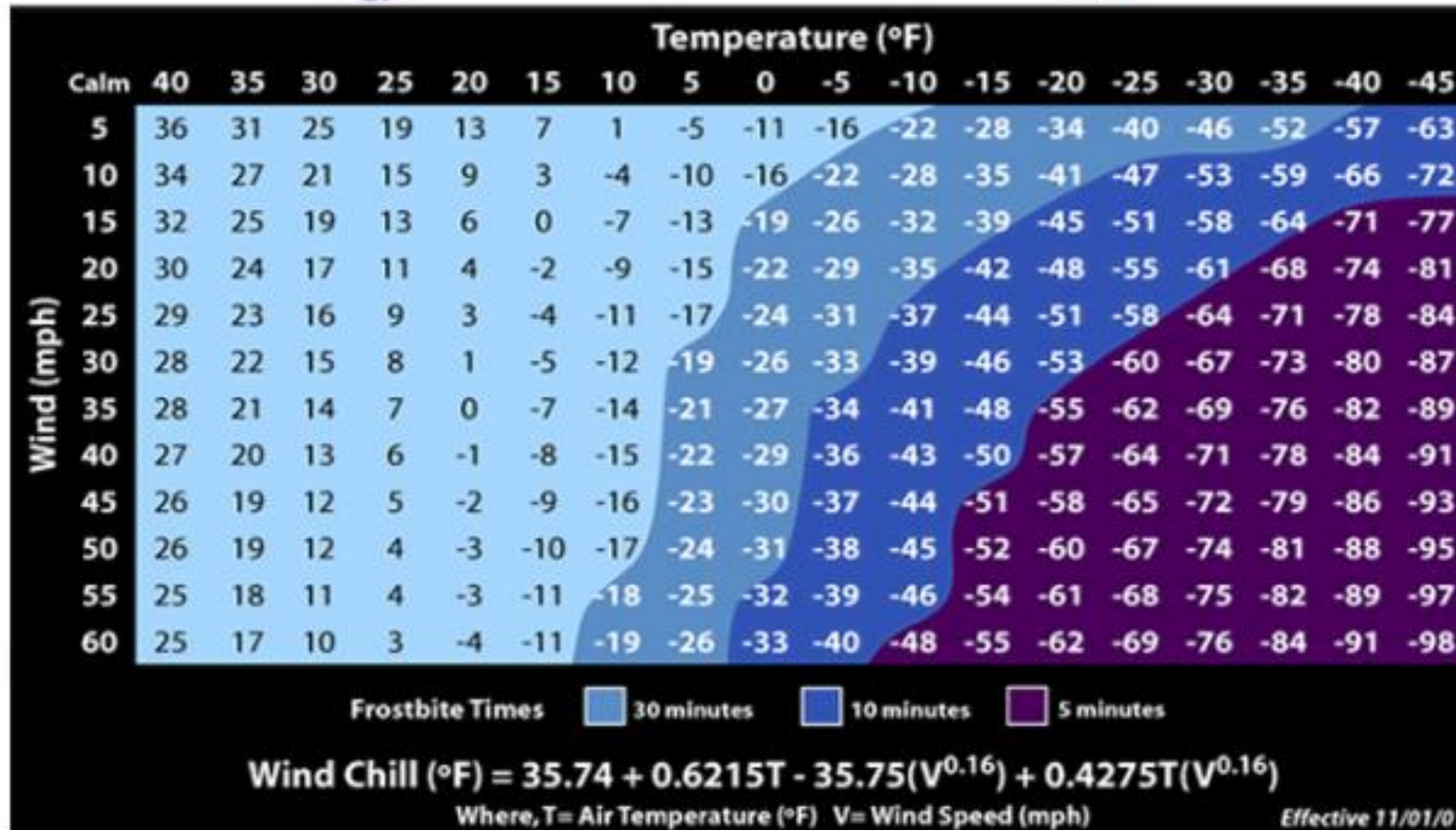
Staff Recommendation No. 4

“Staff recommends the Company work with Staff and stakeholders through technical working groups to address Staff's concerns regarding model evaluation and specification testing for the 2020 IRP.”

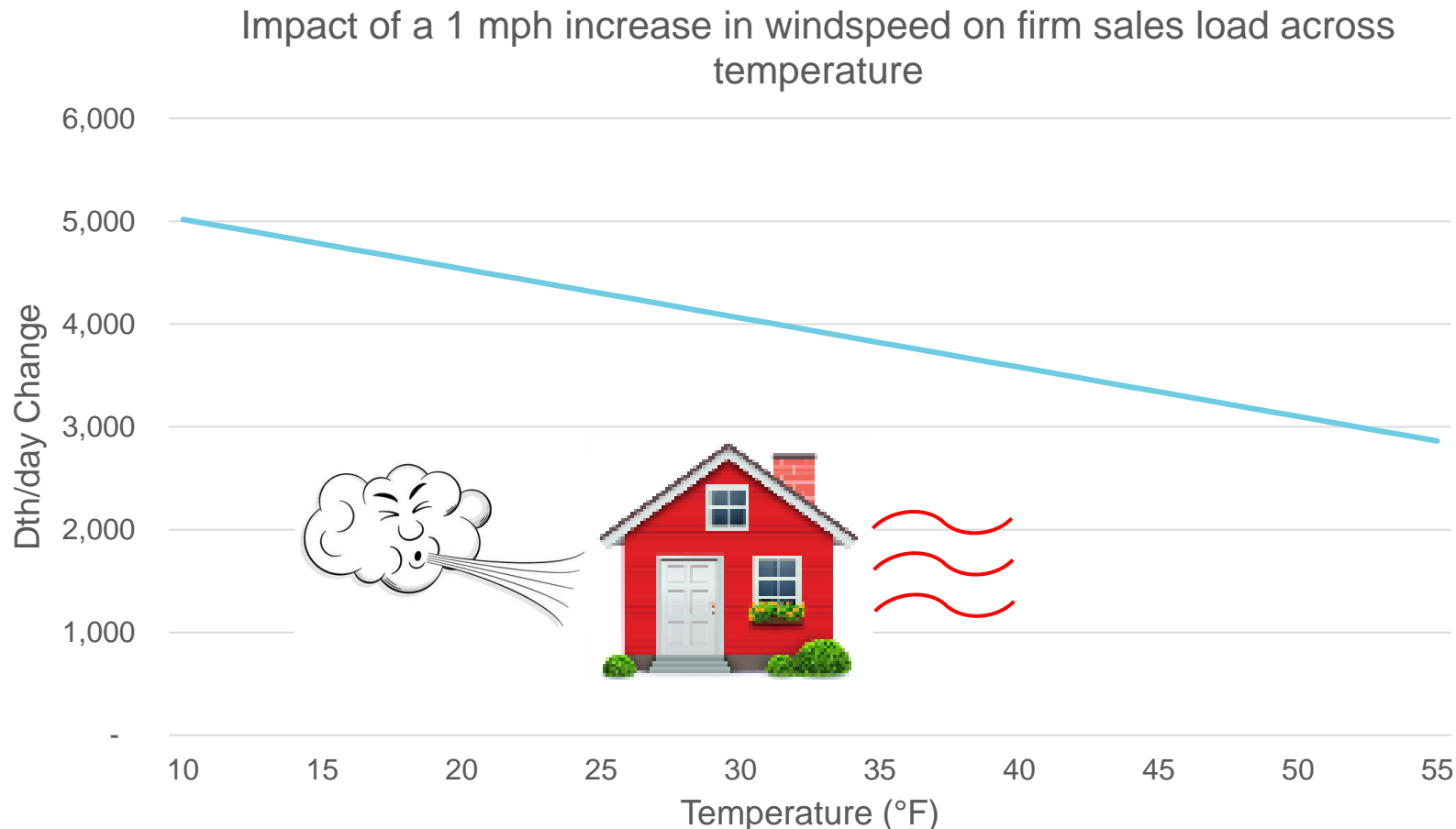
Why Have Interaction Terms With Temperature?



Wind Chill Chart



Why Have Interaction Terms With Temperature?



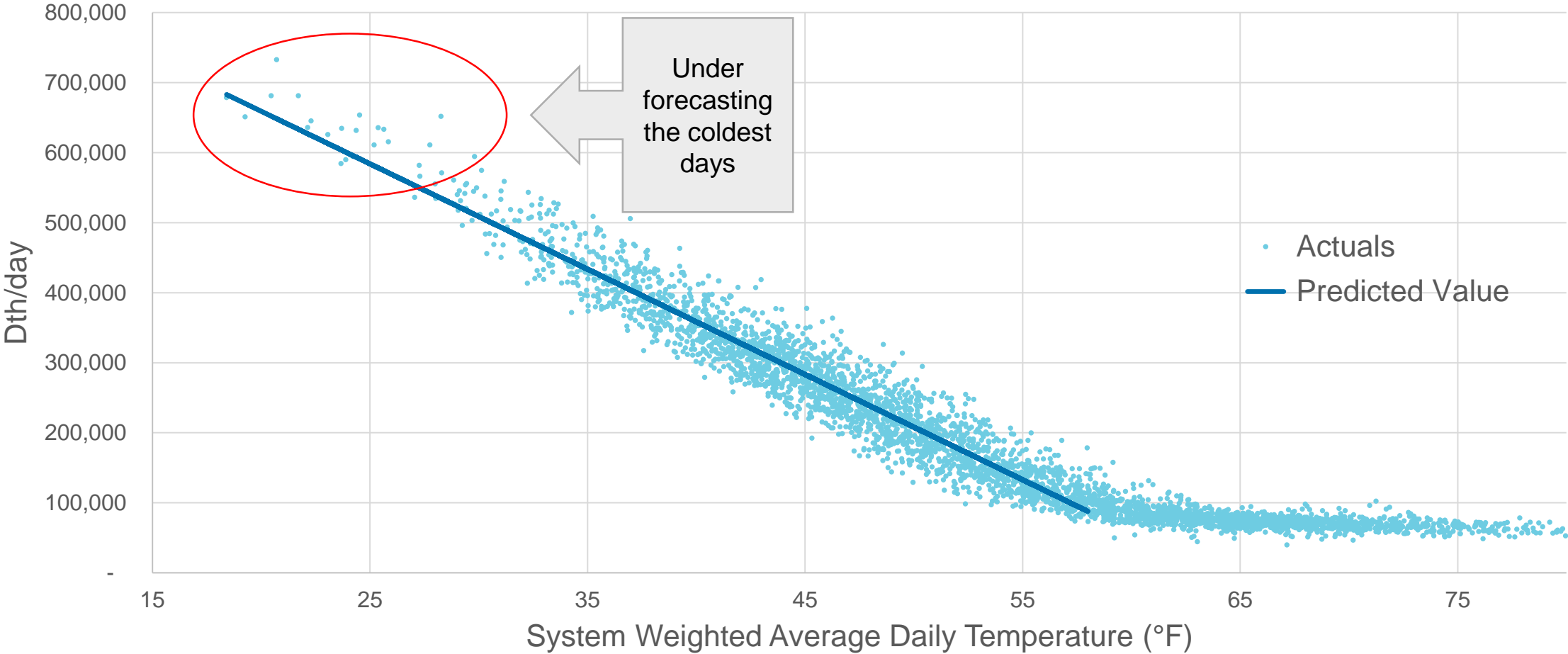
- The impact on load for most of the driver variables fluctuate across temperatures
- For example, 20 mph wind causes more heat loss from a building during a cold winter day (25°F) than the same 20 mph wind during a warm spring or fall day (55°F)
- The positive load impact from wind is greater in magnitude at colder temperatures as the heat loss due to wind is greater at colder temperature

Why Have Interaction Terms With Temperature?

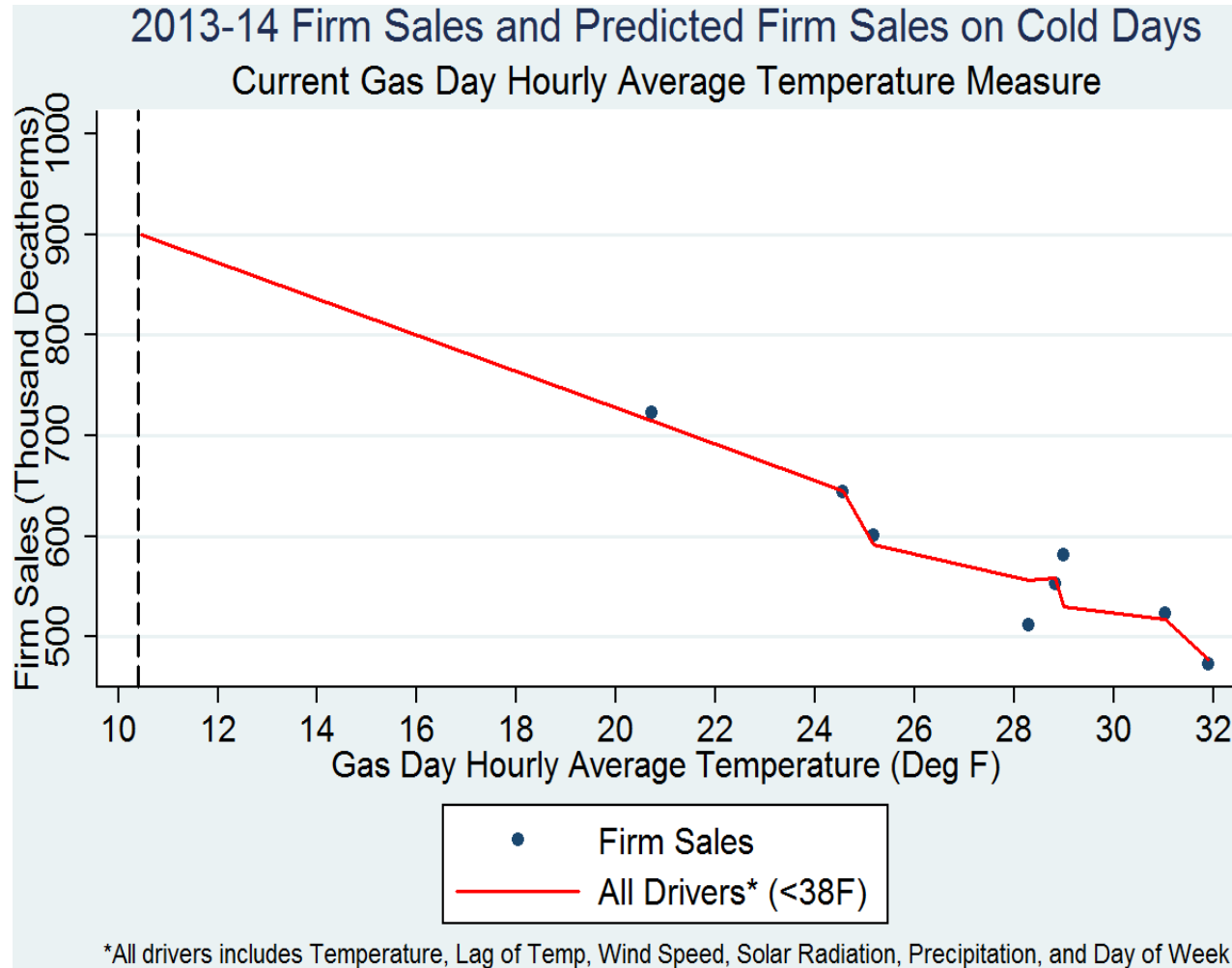
- Another example is the interaction between customer count and temperature
- Adding a customer who has space heating will use more gas to heat their home during very cold days (25°F) when their furnace is running throughout the day
- That same customer will use less gas during spring and fall days (55°F) when their furnace is used intermittently throughout the day
- This temperature interaction is statistically significant with all driver variables with the exception of water heater inlet temperatures and the holiday indicator variable



Simple Temperature Only Model



Previous Analysis of Firm Sales Peak Day Forecast



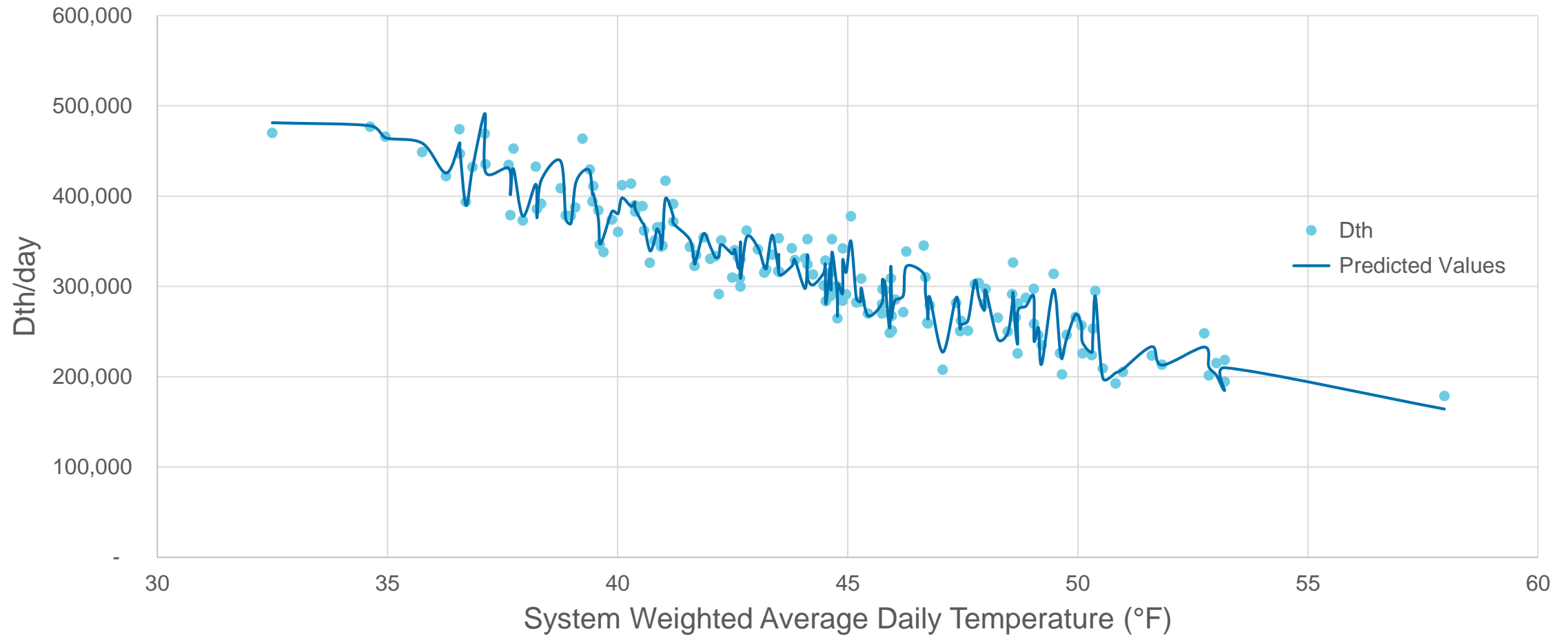
Residuals at Cold Temperatures (Dth/Gas Day)						
All Days Since 1/1/2008						
Temperature Cutoff	Number of Observations (Days)		Temperature Only (<59°F)	Temp Only- Nonlinear (<59°F)	All Drivers- Calendar Day High/Low Avg (<38°F)	All Drivers- Gas Day Hourly Avgs (<38°F)
< 38°F	237	Mean of Residuals	-18,122	-5,752	2	4
		Standard Deviation	40,111	39,315	28,425	26,257
< 32°F	55	Mean of Residuals	-44,036	-7,872	-7,527	-1,904
		Standard Deviation	49,784	53,953	35,594	34,807
< 25°F	12	Mean of Residuals	-85,769	-21,983	-20,655	-10,932
		Standard Deviation	55,426	68,377	38,446	36,659

Moving from average of calendar day high/low to average of gas day hourly measurements further reduces bias and confidence bands in the peak day forecast

*Slide From 2016 IRP TWG

Daily System Load Model

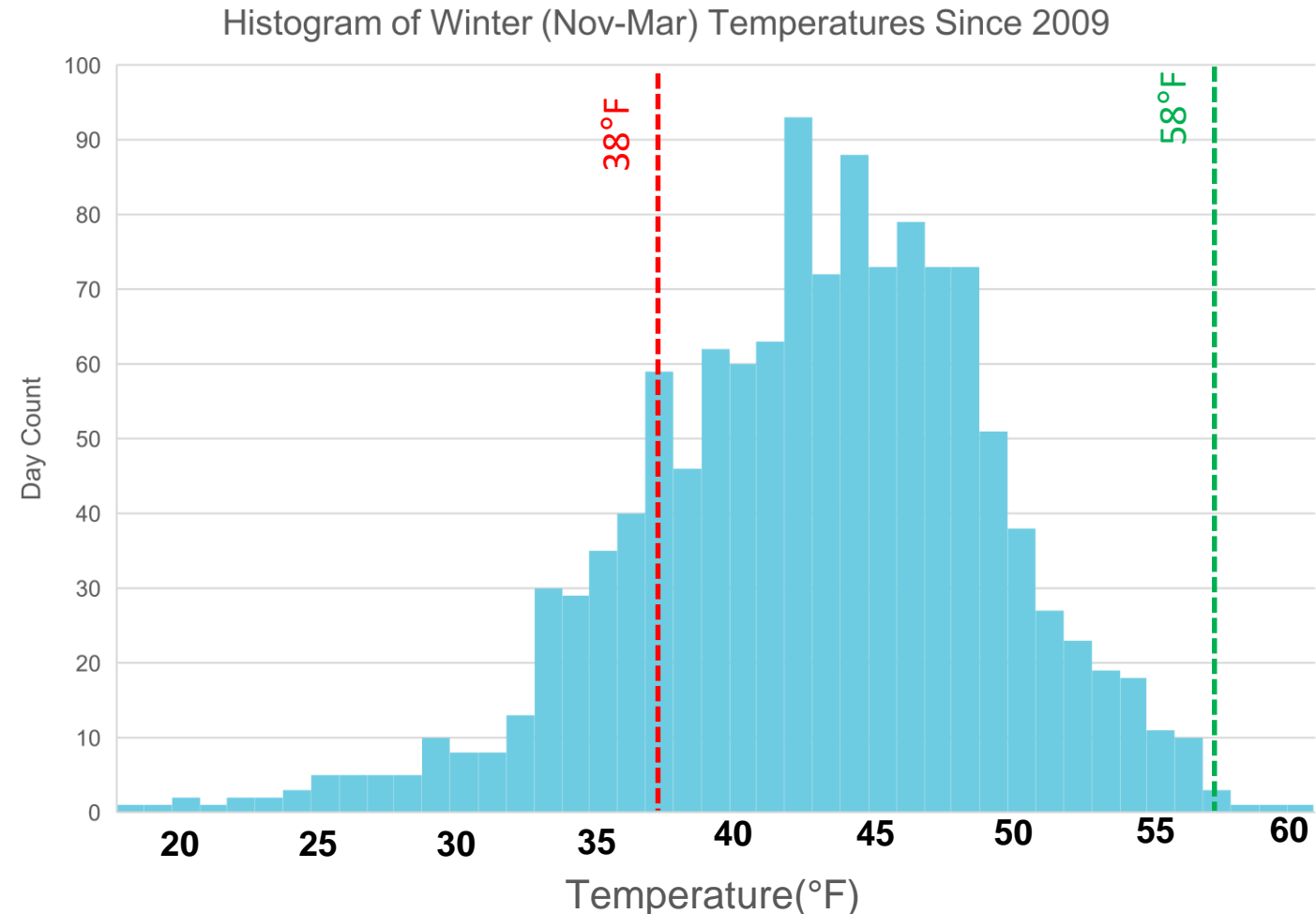
Firm Sales : November 2019-March 2020



Benefits of having Interaction Terms

- Having interaction terms allows for more observations to be included in the training data
- Although we are incorporating more independent variables into the regression, we are actually drastically increasing our degrees of freedom by including more observations

Temperature cut off	# of observations
< 38°F	338
< 58°F; Nov-March	1,735



Regression Results

Linear Regression	Coef.	Robust Std. Err.	t	P> t
Temperature	17,530.49	6,743.85	2.6	0.009
Previous Day Temperature	-8,800.16	301.73	-29.17	0.000
Solar Radiation	-13.42	2.42	-5.55	0.000
Wind Speed	5,497.50	657.94	8.36	0.000
Snow Depth	-26,923.99	5,393.96	-4.99	0.000
Customer Count	2.80	0.47	5.97	0.000
Friday Indicator	-32,051.75	7,212.22	-4.44	0.000
Saturday Indicator	-46,305.20	7,239.25	-6.4	0.000
Sunday Indicator	-43,988.44	6,721.36	-6.54	0.000
Holiday Indicator	-26,013.29	3,629.11	-7.17	0.000
Time Trend	-17,466.71	4,458.50	-3.92	0.000
Bull Run River Temperature	-1,535.16	127.82	-12.01	0.000
Temperature * Previous Day Temperature	141.54	6.53	21.67	0.000
Temperature * Solar Radiation	0.16	0.05	3.04	0.002
Temperature * Wind Speed	-47.92	15.38	-3.12	0.002
Temperature * Snow Depth	697.40	177.77	3.92	0.000
Temperature * Customer Count	-0.05	0.01	-5.16	0.000
Temperature * Friday Indicator	499.65	158.31	3.16	0.002
Temperature * Saturday Indicator	579.50	163.26	3.55	0.000
Temperature * Sunday Indicator	674.01	151.08	4.46	0.000
Temperature * Time Trend	398.48	99.99	3.99	0.000
Constant	-590,018.30	299,682.00	-1.97	0.049

Note that coefficients cannot be interpreted individually.

Marginal Effect of Temperature For the Average January Weekday[†]

Temperature -13,964

[†] Previous Day Temp = 41.3; Solar Radiation = 1,281; Wind Speed = 7.1; River Temp = 40.2; Time = 12; Cust (YE 2020 Com+Res) = 773,388

Marginal Effect	Evaluated at 25°F	Evaluated at 45°F
Previous-Day Temperature	-5,262	-2,431
Wind Speed	4,300	3,341
Solar Radiation	-9.5	-6.36
Customer Count	1.446	0.360
Saturday Indicator	-27,138	-20,228

Stepwise Results

- We ran a stepwise regression in Stata and allowed the model to select from several various interaction terms and non-linear terms
- While the fit of the model across temperatures improved, the prediction of the coldest temperatures did not
- The stepwise process included more variables making the regression less parsimonious
- We also ran a stepwise regression limiting the regression to select only the variables in the current model and the stepwise process selected all variables

Dth	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
TempGHA	36954.28	15223.97	2.43	0.015	7094.523	66814.04
TimeYTempSnowDepth	76.3704	22.65313	3.37	0.001	31.93935	120.8015
RadGHA	-16.6994	2.477622	-6.74	0.000	-21.55892	-11.83988
WindGHA	2939.263	245.1671	11.99	0.000	2458.401	3420.125
CustTempFri	-.0510984	.0295987	-1.73	0.084	-.1091522	.0069555
Cust	5.734666	1.263684	4.54	0.000	3.25612	8.213211
FriDum	-1655271	884143.9	-1.87	0.061	-3389400	78857.59
SatDum	-48022.97	6786.114	-7.08	0.000	-61333.01	-34712.92
SunDum	-1829728	723226.8	-2.53	0.011	-3248239	-411216.4
TimeYTempWind	-7.092046	2.186535	-3.24	0.001	-11.38064	-2.803454
TimeY	-127980.4	21546.07	-5.94	0.000	-170240.1	-85720.74
BullRunTemp	27690.53	13268.46	2.09	0.037	1666.248	53714.81
CustFri	2.545935	1.371109	1.86	0.064	-.1433098	5.235179
CustBullRunTemp	-.047465	.0207636	-2.29	0.022	-.0881901	-.00674
TempRad	.9707276	.1376488	7.05	0.000	.700748	1.240707
CustTempSun	-.0627125	.025693	-2.44	0.015	-.1131059	-.0123191
TempCust	-.0846785	.0232752	-3.64	0.000	-.1303296	-.0390274
TempFri	33020.92	19081.69	1.73	0.084	-4405.232	70447.07
TempSat	618.3824	152.7248	4.05	0.000	318.8335	917.9314
TempSun	40653.95	16529.08	2.46	0.014	8234.394	73073.51
CustHol	-.0364096	.0050943	-7.15	0.000	-.0464013	-.0264179
TempTimeY	432.526	164.8659	2.62	0.009	109.1639	755.888
TimeYLagTemp	221.9801	115.4547	1.92	0.055	-4.46878	448.4289
TimeYWind	388.291	101.466	3.83	0.000	189.2791	587.3029
CustLagTemp	-.0146572	.0010564	-13.87	0.000	-.0167293	-.0125852
TimeYSnowDepth	-3057.481	637.1631	-4.80	0.000	-4307.19	-1807.771
TimeYCust	.1386555	.0279082	4.97	0.000	.0839173	.1933937
TimeYFri	-25687.77	12501.31	-2.05	0.040	-50207.39	-1168.15
CustTempRad	-1.05e-06	1.75e-07	-5.98	0.000	-1.39e-06	-7.04e-07
TimeYSun	-28560.41	10478.25	-2.73	0.006	-49112.08	-8008.743
CustSun	2.801636	1.124134	2.49	0.013	.5968003	5.006472
TimeYBullRunTemp	625.7512	206.2849	3.03	0.002	221.1513	1030.351
TimeYsq	-2682.688	622.3484	-4.31	0.000	-3903.341	-1462.036
TempTimeYsq	28.24013	11.72797	2.41	0.016	5.237299	51.24297
TimeYTempLagTemp	-4.828661	2.491181	-1.94	0.053	-9.714776	.057453
TimeYTempFri	522.0378	270.9	1.93	0.054	-9.295983	1053.372
CustTempLagTemp	.0002494	.0000231	10.81	0.000	.0002041	.0002946
TimeYTempSun	638.3765	239.0104	2.67	0.008	169.5901	1107.163
_cons	-2428121	821464.2	-2.96	0.003	-4039312	-816930.1

Validating Regression Specification

- Out of Sample Forecasting Days with Temp less than 30°F (2016-2017 Heating Season)

How far off are we at predicting the coldest temperatures?

	2016 (%)	2018 (%)
Average Abs Error	5.95%	3.13%
Min Abs Error	0.56%	0.17%
Max Abs Error	12.24%	8.89%

Observations < 30 °F = 13

Are we under or over forecasting at the coldest temperatures?

	2016 (%)	2018 (%)
Average Bias	-5.21%	-0.69%
Max Over Forecast	-12.24%	-8.89%
Max Under Forecast	4.78 %	6.90%

Negative(-) means over forecast
Positive(+) means under forecast

*Slide From 2018 IRP TWG

Monte Carlo Simulation

Monte Carlo Simulation

Goals of the Simulation

- Produce a reasonable distribution of key load drivers which can be a major source of variability and uncertainty
- Use modeling techniques to incorporate key correlation across the different driver variables

Mechanics

- The simulation is conducted in SAS software to randomly generate driver variables based on a specified distribution and necessary inputs (e.g. mean and standard deviation)
- This simulation focuses on the very tail end (i.e. 99th Percentile) for peak planning
- Given that the marginal resources (e.g. Mist Recall) for meeting firm sales peak day requirement can be acquired in small increments, the volatility of a stochastic process can cause different outcomes, especially at the tail end of a normal distribution
- To ensure stability in this process, we run one million draws for each forecast year

Monte Carlo Variables

Variable	Regression Model	Distribution Description for Simulation
Temperature of the coldest day in a heating season	No regression modeling	Normal distribution created from available history starting in gas year 1938-39, when PDX started recording min and max temperatures. Simulated coldest temperatures are bounded at -5°F
Previous-Day Temperature	The percentage difference (logged difference) between the previous day's temperature and the coldest day's temperature is modeled as a function of the coldest day	Normal distribution around the predicted value and the standard error of the predicted value
Month	No regression modeling; Used for solar radiation and water inlet temperature modeling	Discrete probability of month containing the coldest day based on history (Nov-Feb)
Day of the Week	No regression modeling	Discrete 1-in-7 probability for the day of the week
Wind	Modeled as a function of temperature using daily weather data beginning in 1985	Normal distribution around the predicted value and the standard error of the predicted value
Solar Radiation	Modeled as a function of temperature and month using daily weather data beginning in 1985	Normal distribution around the predicted value and the standard error of the predicted value

This is the same methodology used in the 2018 IRP with the exception of excluding a simulation and distribution around the customer count forecast.

Monte Carlo Variables

Variable	Regression Model	Distribution Description for Simulation
Snow Day	No regression modeling; used for snow depth simulation modeling	Binary variable for probability of non-zero snow depth using daily weather data beginning in 1985 for temperatures below 40°F
Snow Depth	Modeled as a function of temperature using data beginning in 1985	Normal distribution around the predicted value and the standard of the predicted value; multiplied by binary snow day variable
Water Heater Inlet Temperature (i.e., Bull Run River Temperature)	No regression modeling	Normal distribution around a monthly mean and standard deviation within that month
Model Error	No regression modeling	Normal distribution based on the standard error of the individual predicted value of daily firm sales load from the predicted value based on simulated variables and the daily system load model

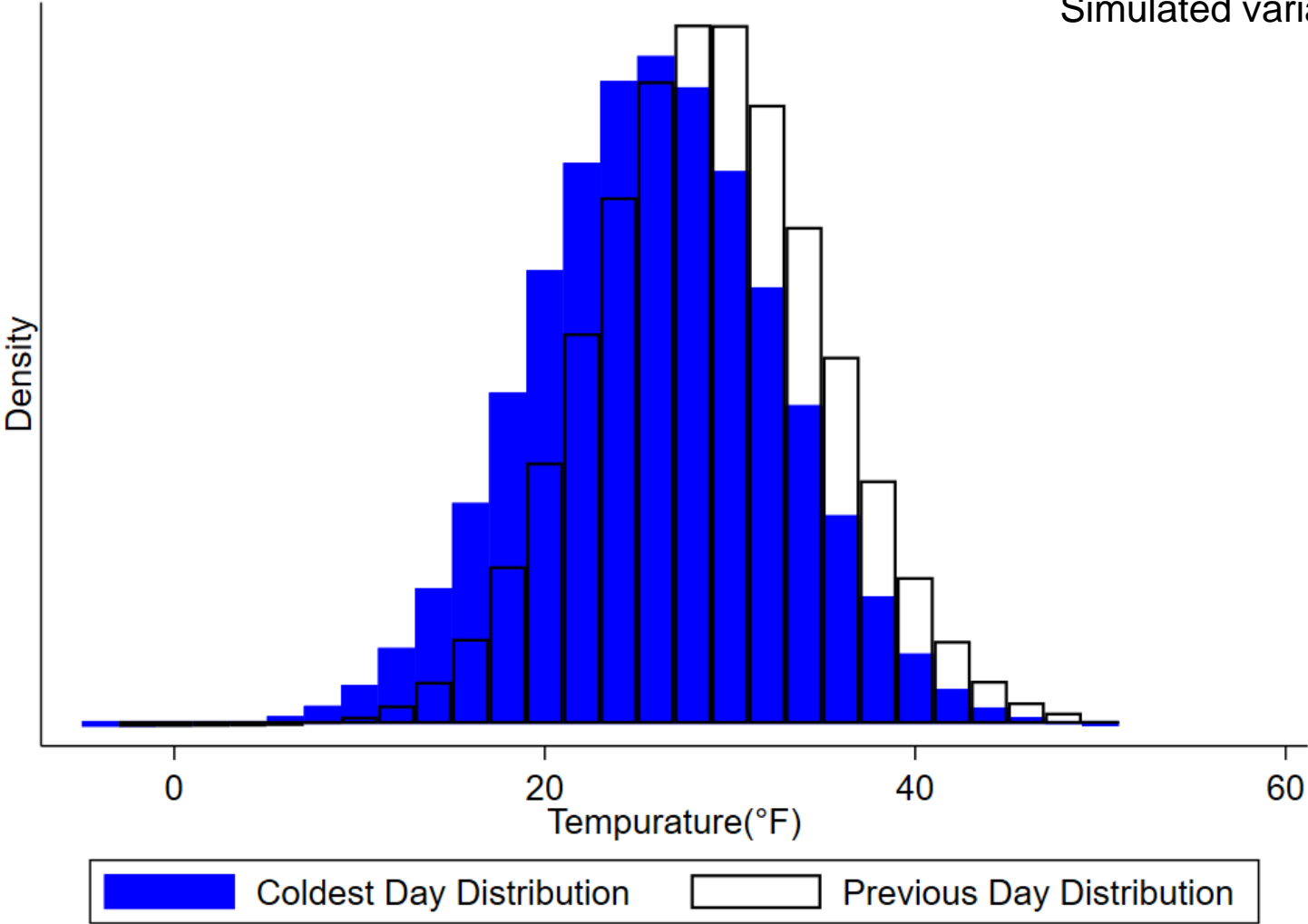
This is the same methodology used in the 2018 IRP with the exception of excluding a simulation and distribution around the customer count forecast.

SAS Code

```
*SECTION 03: MONTE CARLO SIMULATION FOR EACH FORECAST YEAR;
*****
☐ %Macro Monte_Carlo(GasYear=,Cust=,Custstd=);
  *Create base file of simulated Temperature and other variables that are uncorrelated with Temperature;
  Data Sim1;
  format dataType $16.;
  do _n_ = 1 to &Draws.;
  dataType = 'SimData';
  *Month probability is based on the percentage of the coldest day occurs in that month since the start of data;
  Month = rand('Table', &M1pct., &M2pct., 0,0,0,0,0,0,0,0,0, &M11pct., &M12pct.);
  *Bull Run Temp is normally distributed around the mean of the temperature of that month;
    if Month = 11 then BullRunTemp = rand('NORMAL',&WT11mean., &WT11std.);
    if Month = 12 then BullRunTemp = rand('NORMAL',&WT12mean., &WT12std.);
    if Month = 1 then BullRunTemp = rand('NORMAL',&WT1mean., &WT1std.);
    if Month = 2 then BullRunTemp = rand('NORMAL',&WT2mean., &WT2std.);
  *Create Month Dummies (used for solar radiation simulation);
    if Month = 11 then dmonth11 = 1; else dmonth11 = 0;
    if Month = 12 then dmonth12 = 1; else dmonth12 = 0;
    if Month = 1 then dmonth1 = 1; else dmonth1 = 0;
    if Month = 2 then dmonth2 = 1; else dmonth2 = 0;
  *Day of the week has a 1 in 7 chance for each day of the week. Fri,Sat, and Sun dummies are created from the simulated DOW.;
  DOW = rand('Table',1/7,1/7,1/7,1/7,1/7,1/7,1/7);
    if DOW = 6 then FriDum = 1; else FriDum = 0;
    if DOW = 7 then SatDum = 1; else SatDum = 0;
    if DOW = 1 then SunDum = 1; else SunDum = 0;
  HoldDum = 0;
```

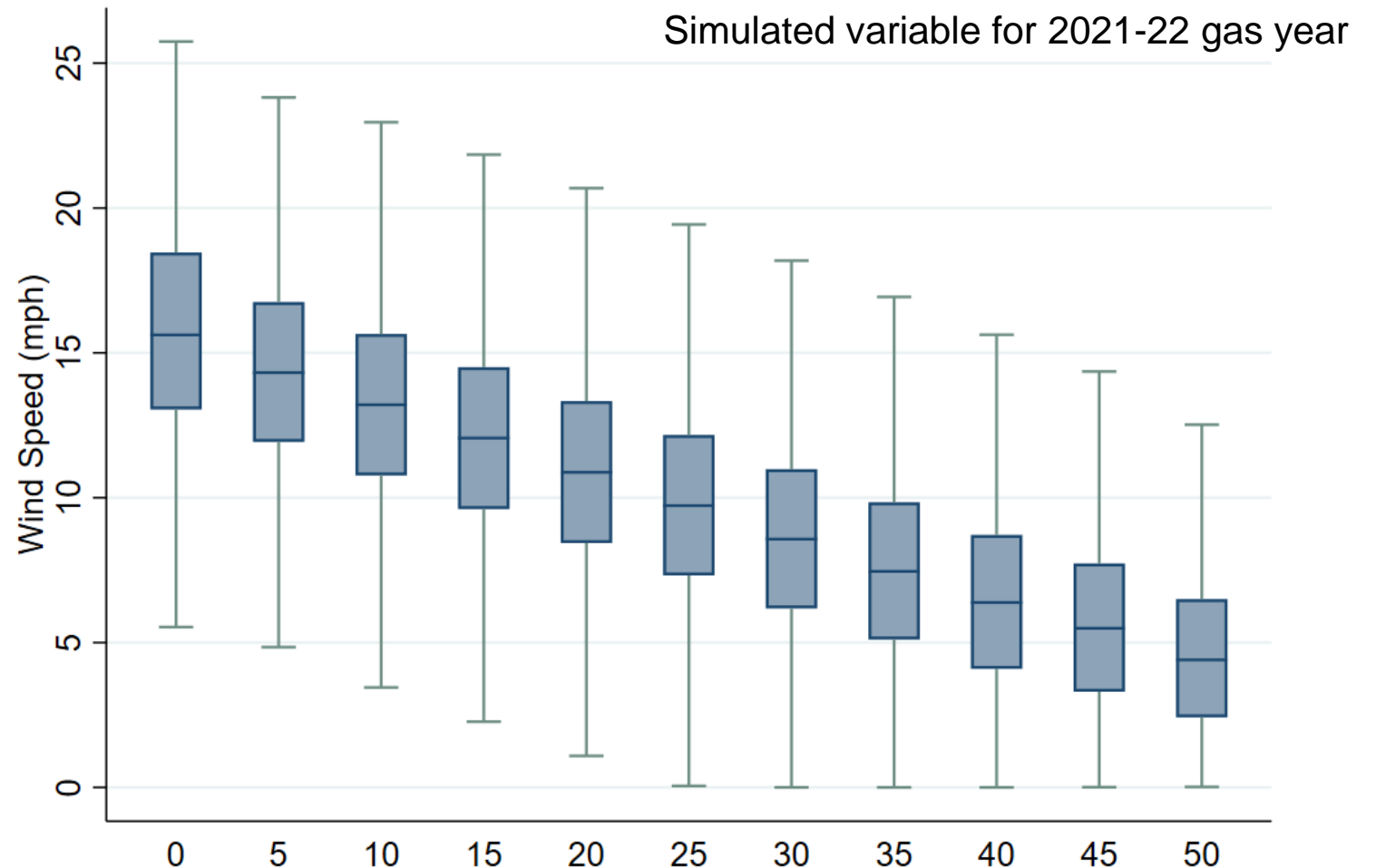

Temperature Histogram

Simulated variable for 2021-22 gas year



Wind Speed Distribution Across Temperatures

- Wind speed is correlated with temperature
- Wind speed is modeled as a function of temperature
- Values are simulated with a normal distribution around the predicted value calculated from the simulated coldest day temperature
- This graph is a box and whisker chart showing the distribution of wind speed across temperatures

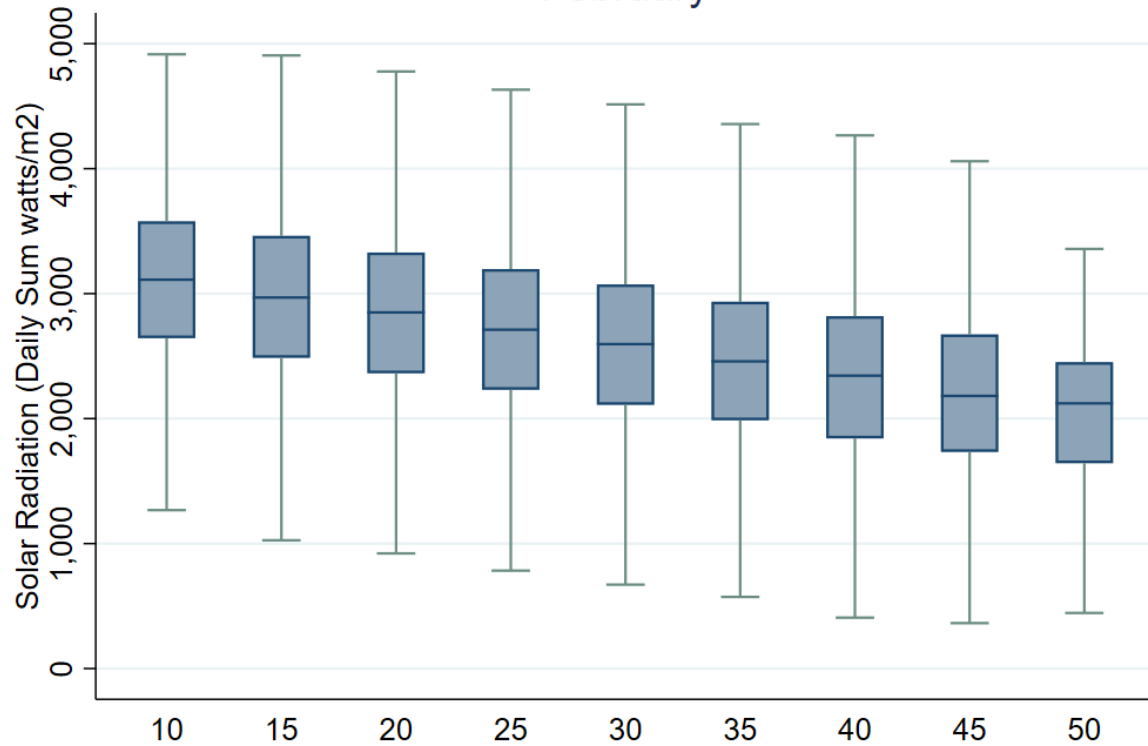


Notes: Temperatures were rounded to the nearest multiple of 5 for graphing purposes; excludes outside values

Solar Distribution Across Temperatures and Month

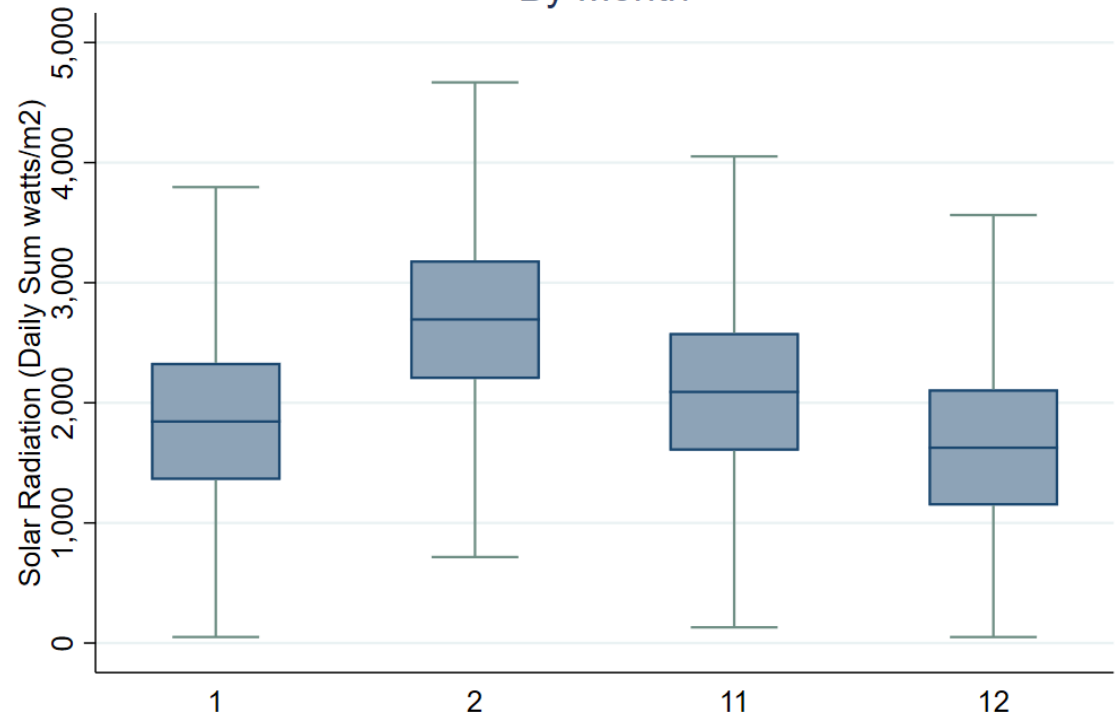
Simulated variable for 2021-22 gas year

February



Notes: Temperatures were rounded to the nearest multiple of 5 for graphing purposes; excludes outside values

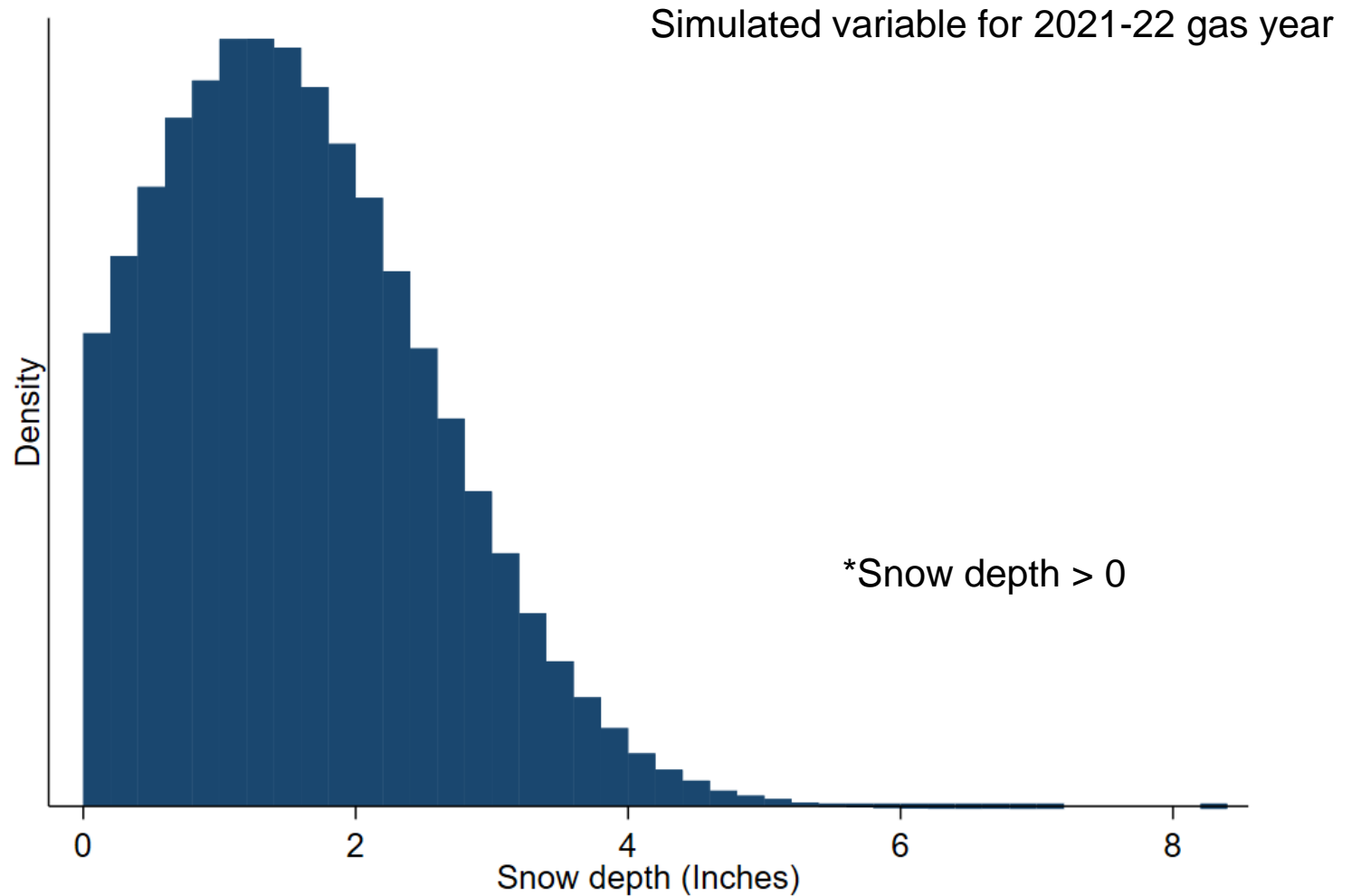
By Month



Notes: excludes outside values

Snow Depth Histogram

- The majority of the time, we do not have lasting snow to accumulate enough for measurable snow depth
- When we do have snow depth, the distribution skews right as heavy snow events are rare



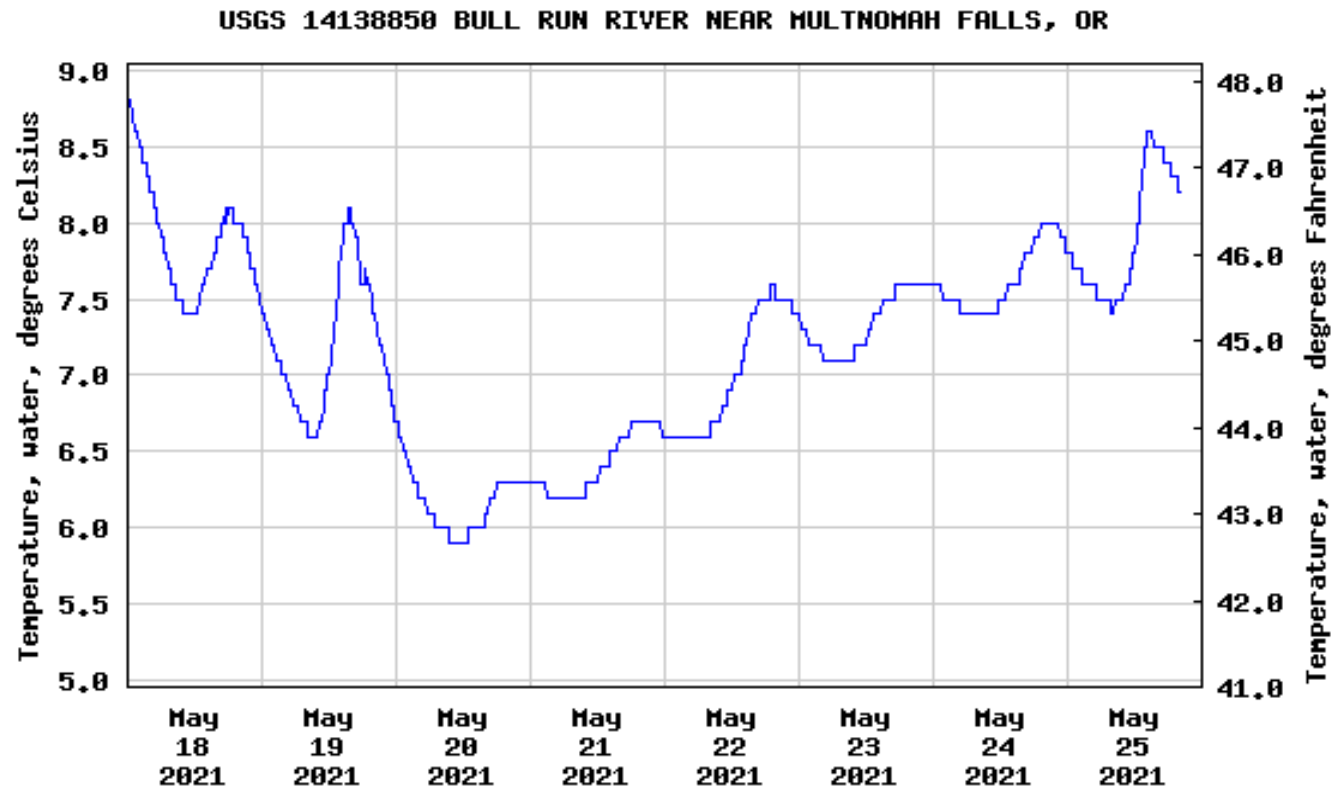
Water Heater Inlet Temperature

Simulated variable for 2021-22 gas year

- The Bull Run River is Portland's main water supply
- The water temperature variation is seasonal and changes gradually throughout the year
- Other factors beyond air temperature impact water temperature (e.g., previous winter snow pack)
- Creating a distribution by month is sufficient for our modeling purposes

Temperature, water, degrees Celsius

Most recent instantaneous value: 8.2 05-25-2021 20:00 PDT



----- Provisional Data Subject to Revision -----

Source: waterdata.usgs.gov

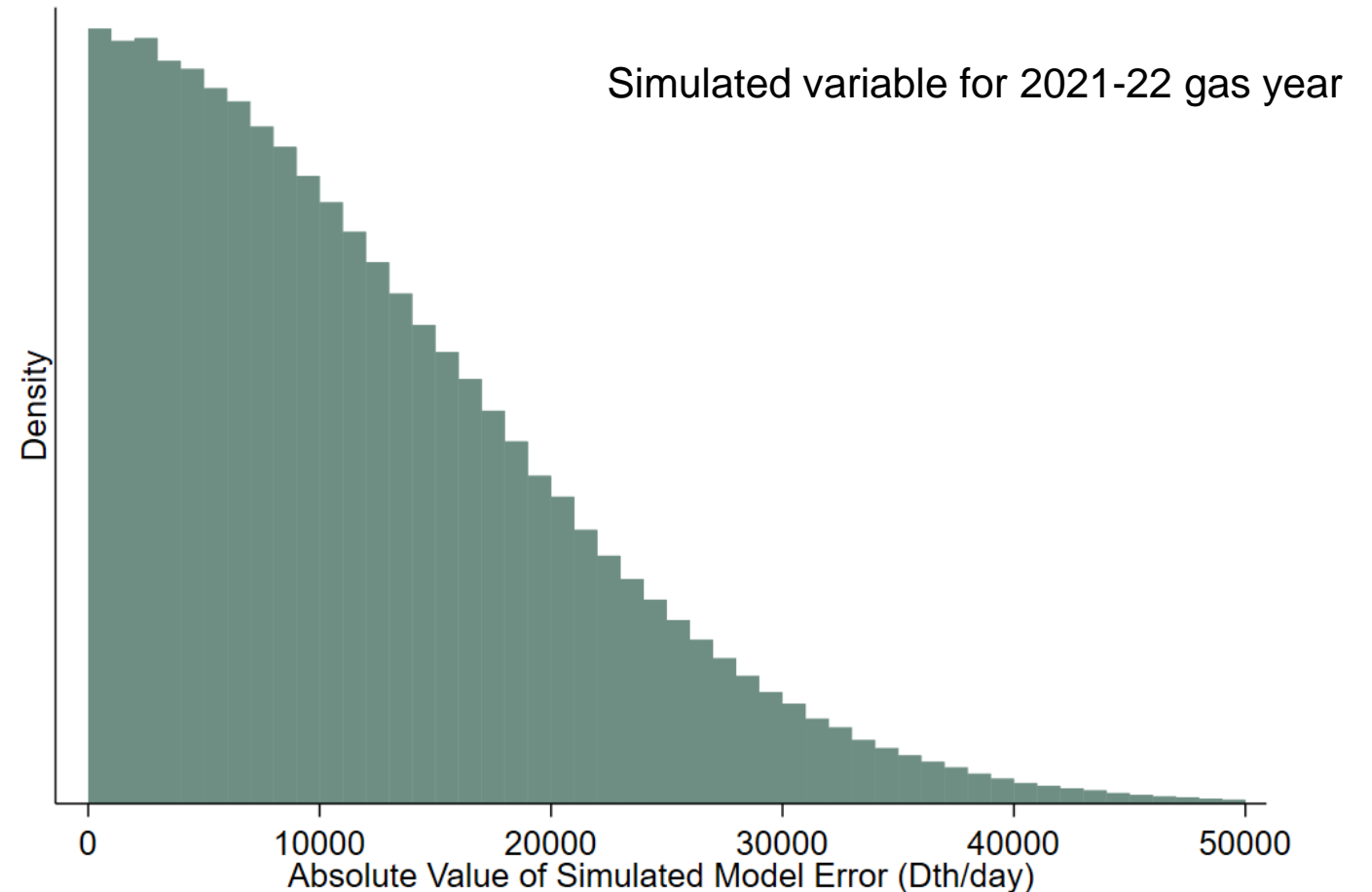
Week Day Frequency

Day of the Week has a 1-in-7 chance of occurring

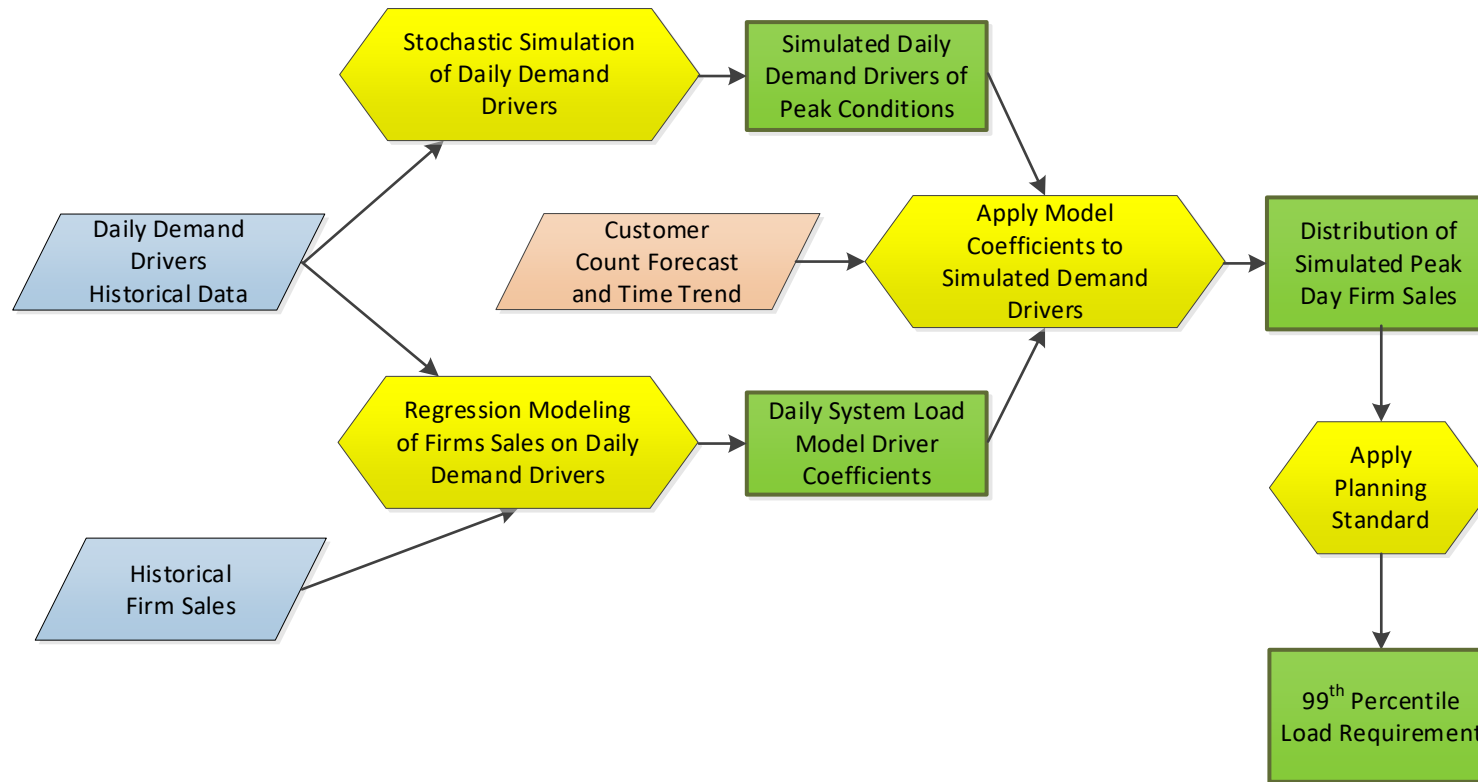
Day of the Week	Freq.	Percent	Cum.
1	143,170	14.32	14.32
2	142,706	14.27	28.59
3	142,625	14.26	42.85
4	142,957	14.30	57.15
5	142,742	14.27	71.42
6	142,636	14.26	85.68
7	143,164	14.32	100.00
Total	1,000,000	100.00	

Model Error is Included in the Monte Carlo

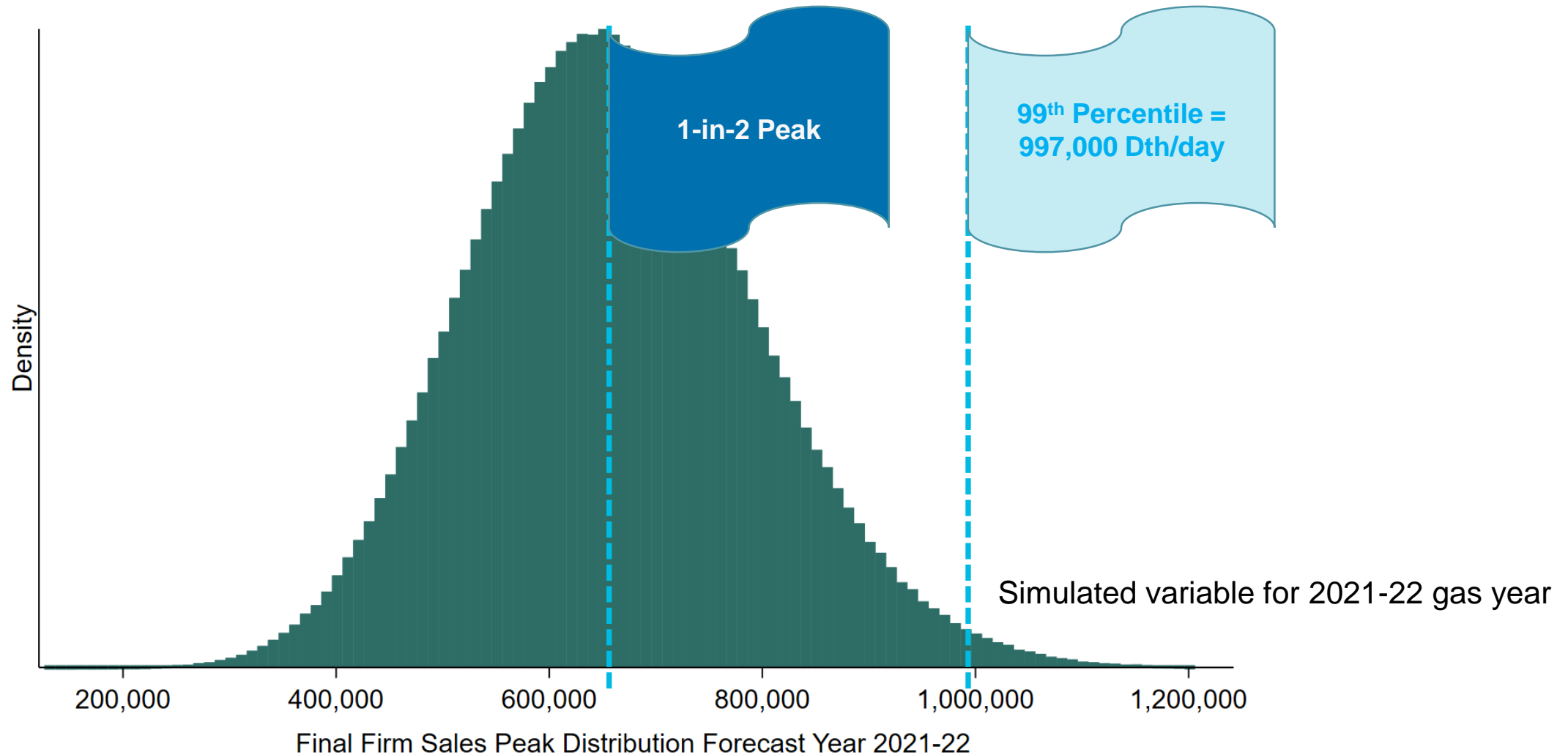
- We know our regression modeling is good, but not perfect
- We incorporate a simulated error normally distributed around the predicted value
- This histogram shows the absolute value of the error, meaning half of the time the error will increase the final simulated value and half of the time it will decrease the simulated value



Firm Sales Peak-Day Load Forecast Flow Chart



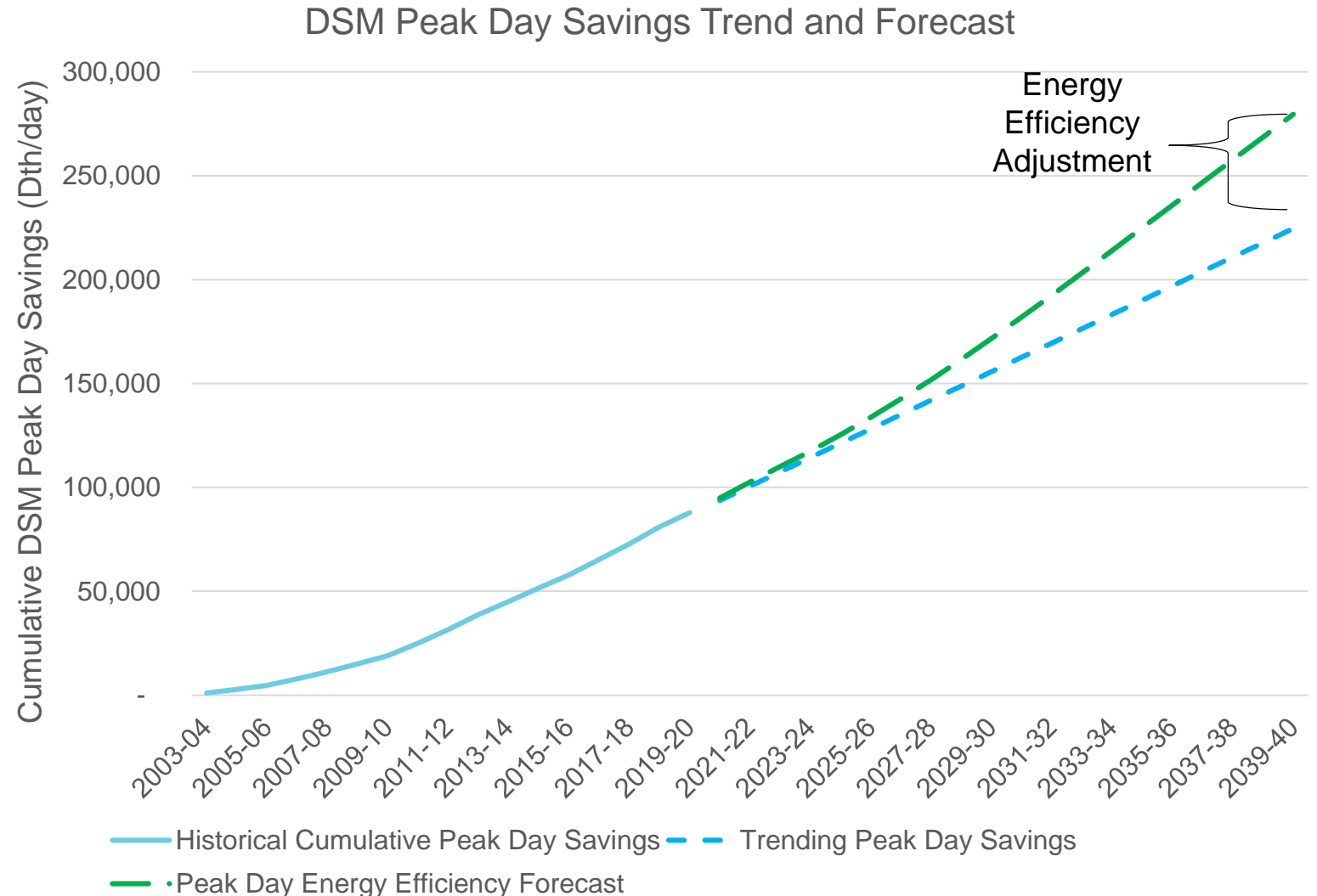
Firm Sales Peak-Day Histogram



Peak-Day Load Forecast

Energy Efficiency Adjustment

- Underlining trends are included in the regression model, which include any energy efficiency (EE) in the historical data
- To avoid double counting trends in peak therms saved from EE, we project forward a trend of cumulative peak savings based on historical savings
- We make an EE adjustment to the 99th percentile equal to the difference between the EE trend and the EE forecast

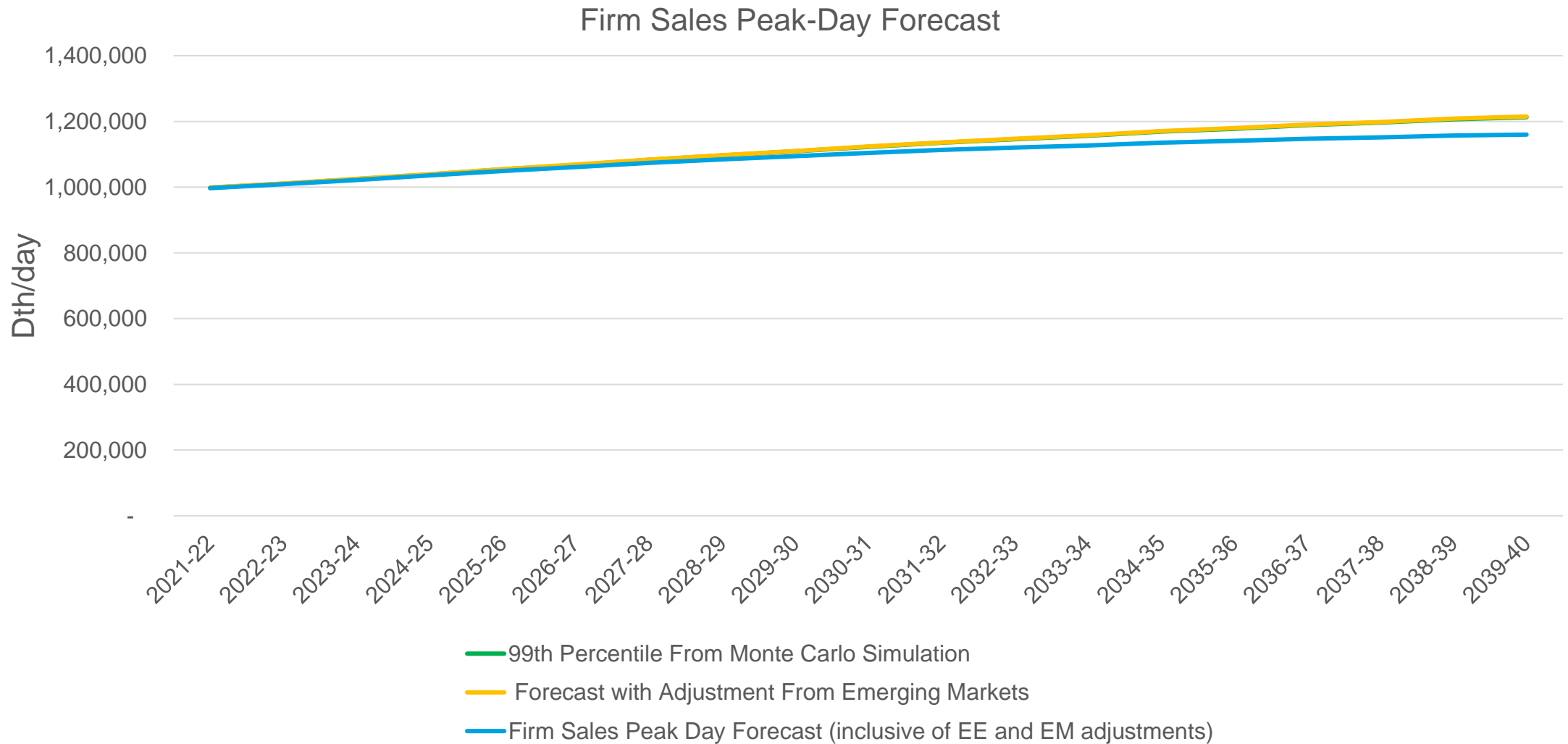


Emerging Markets Adjustment

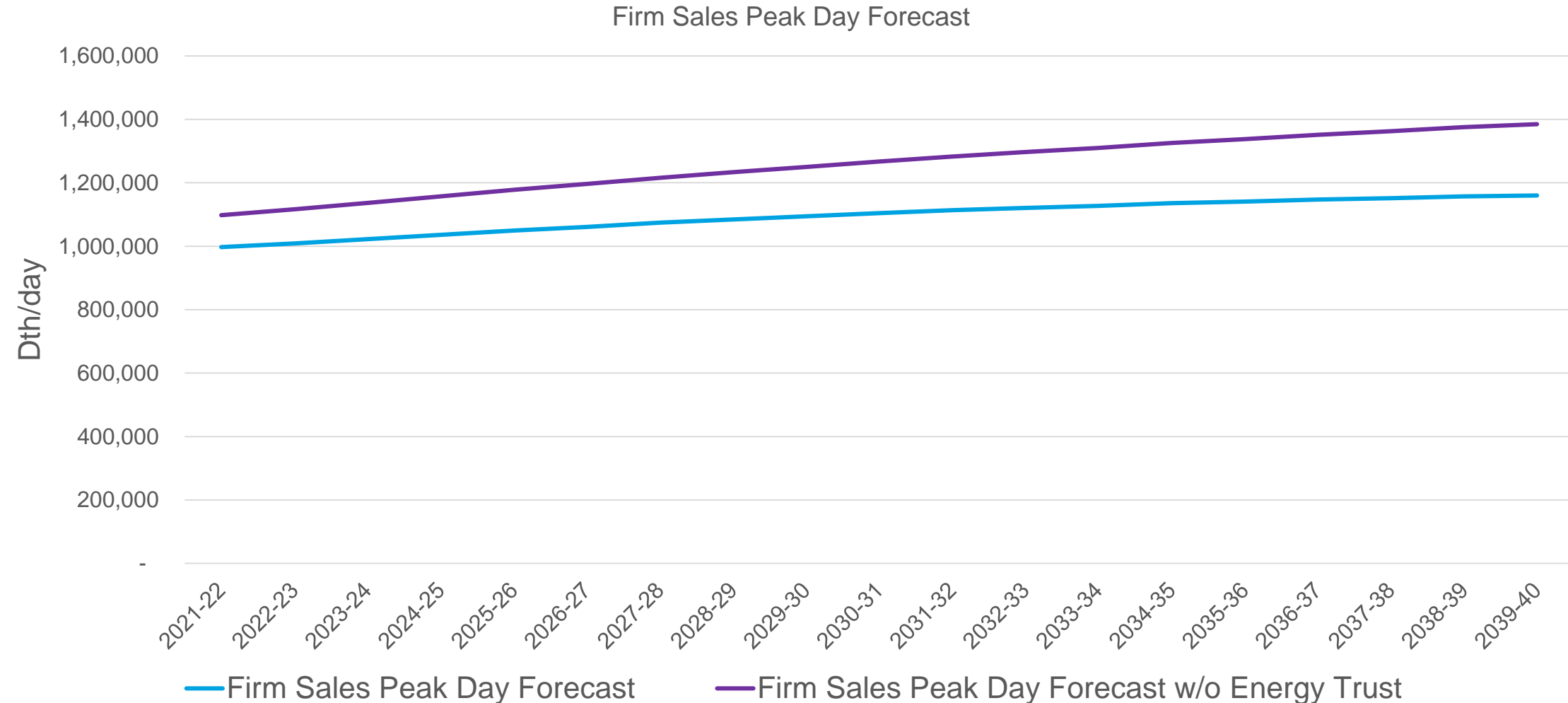
- We make an adjustment for the peak day contribution to firm sales load from emerging markets (i.e., natural gas demand from sources not previously captured in the data)
- This currently includes emerging market demand forecast from compressed natural gas (CNG) vehicles
- The current emerging markets annual forecast is very small compared to the rest of our load
- The firm sales peak day contribution is even smaller as demand from CNG vehicles is not sensitive to temperature and makes up <math><0.1\%</math> of the firm sales peak day load



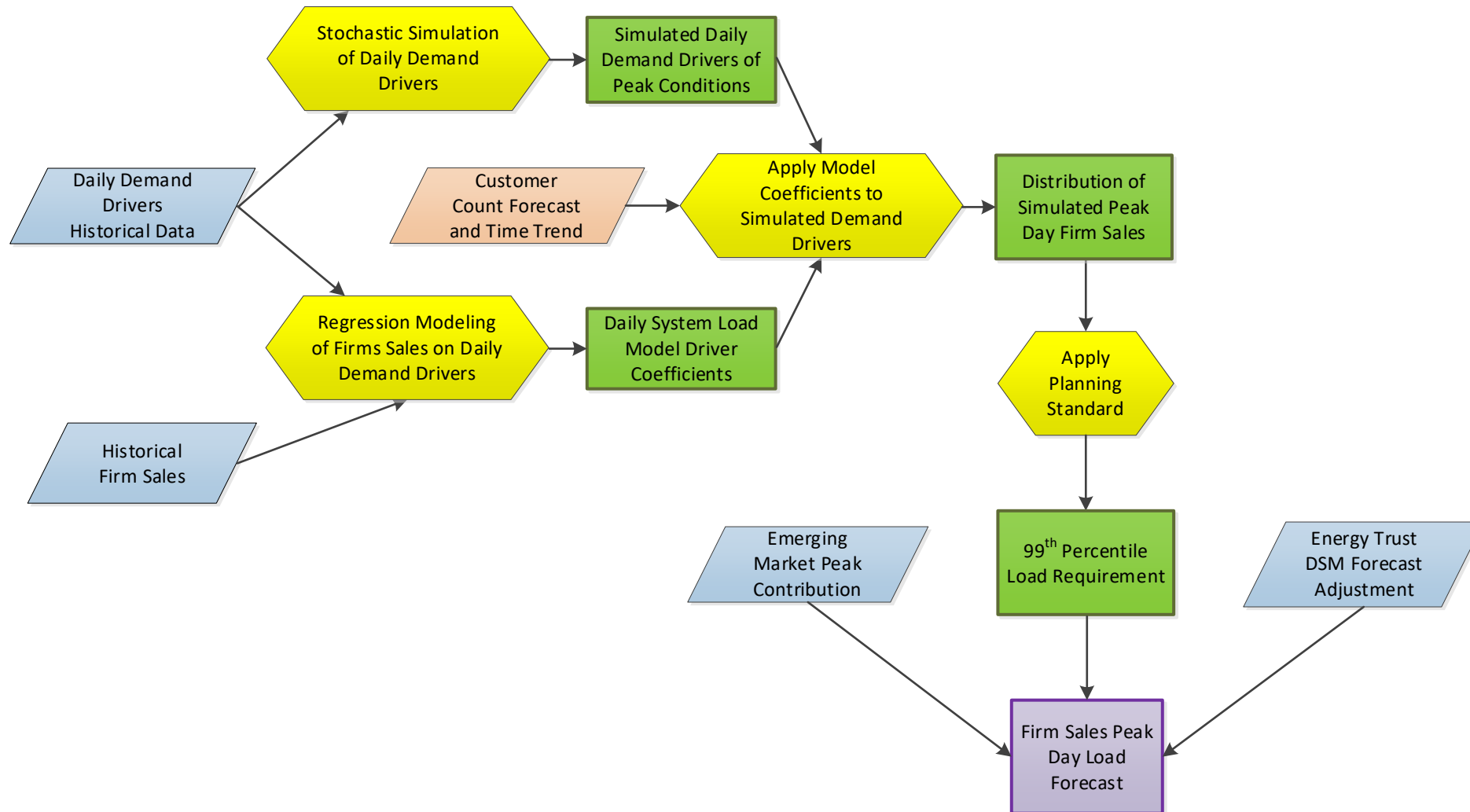
Peak-Day Forecast



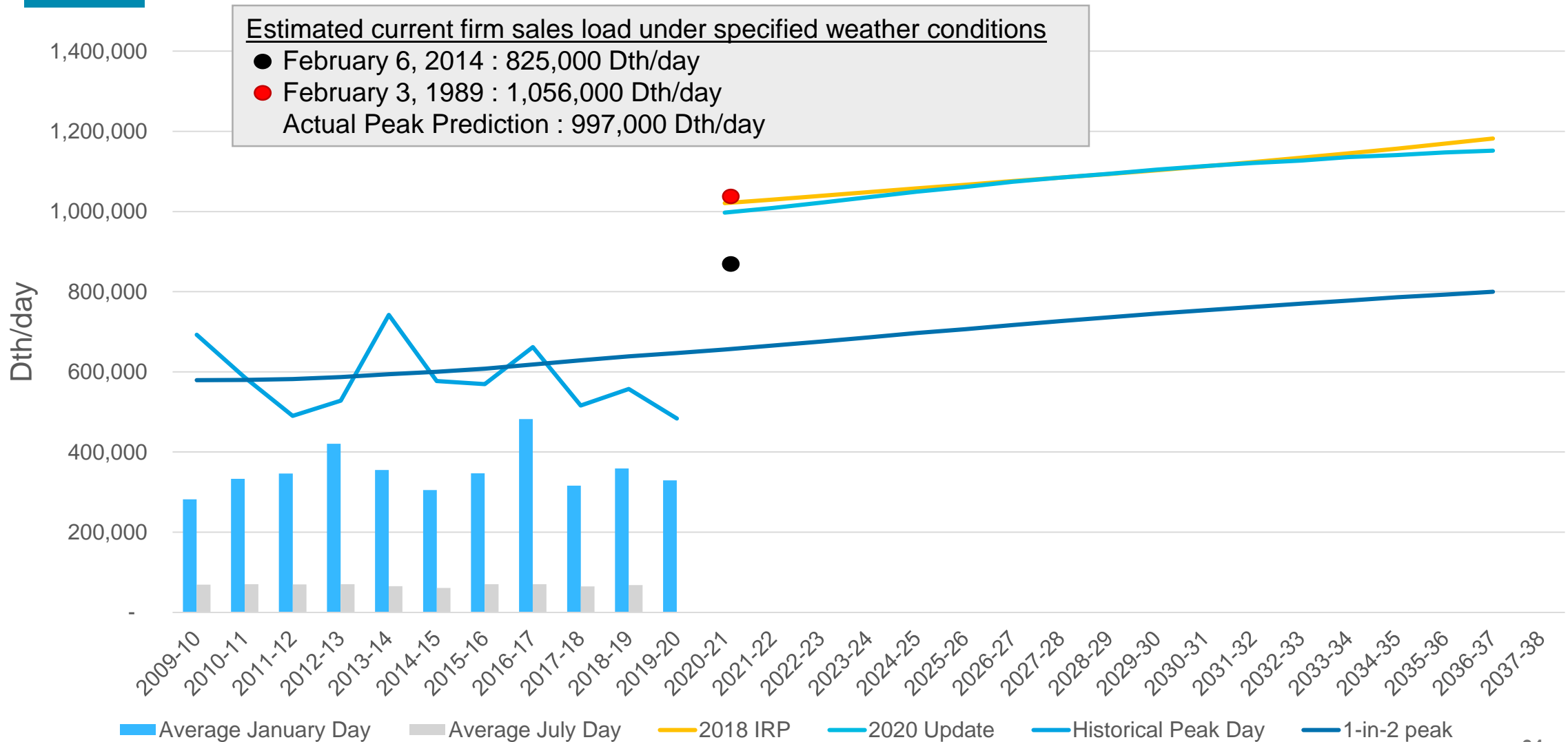
The Benefits of Energy Efficiency for Peak-Day Savings



Firm Sales Peak-Day Load Forecast Flow Chart

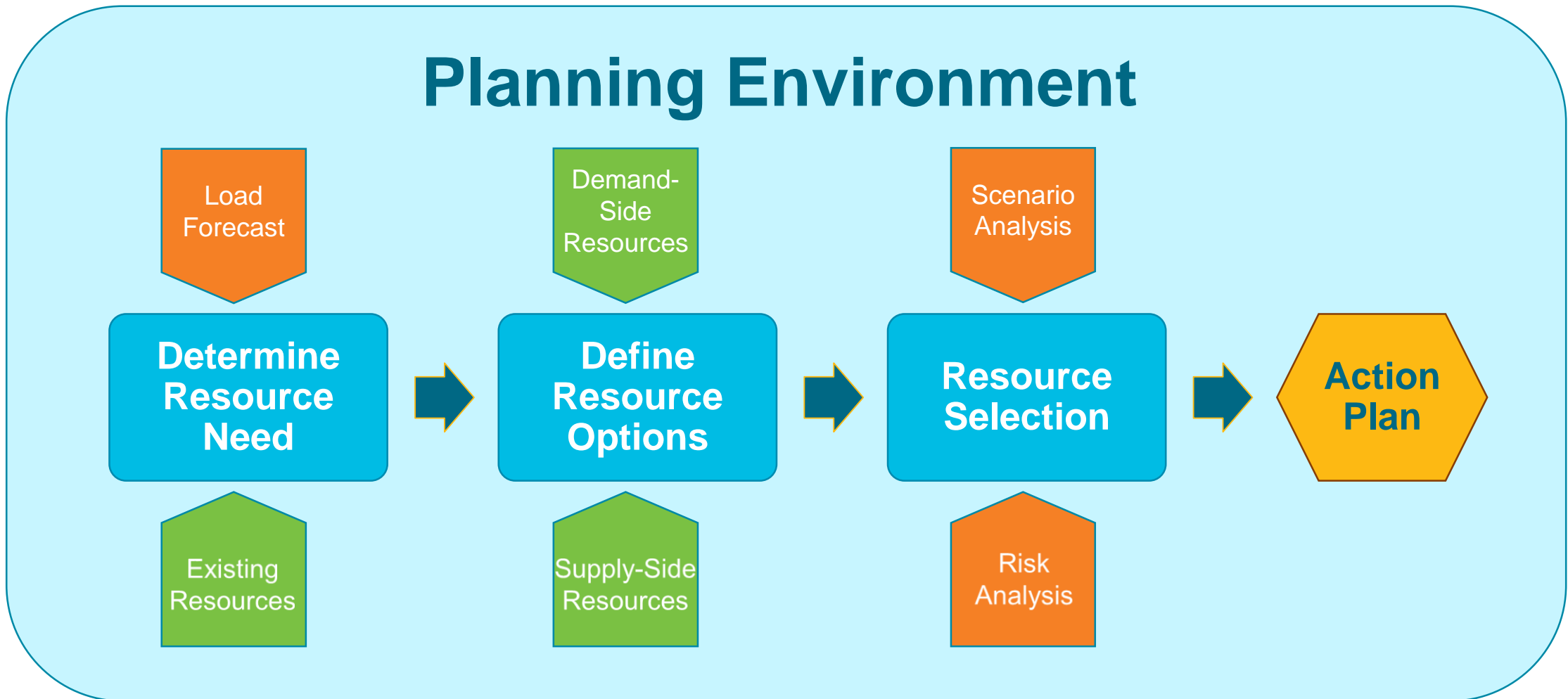


Peak-Day Firm Sales Forecast



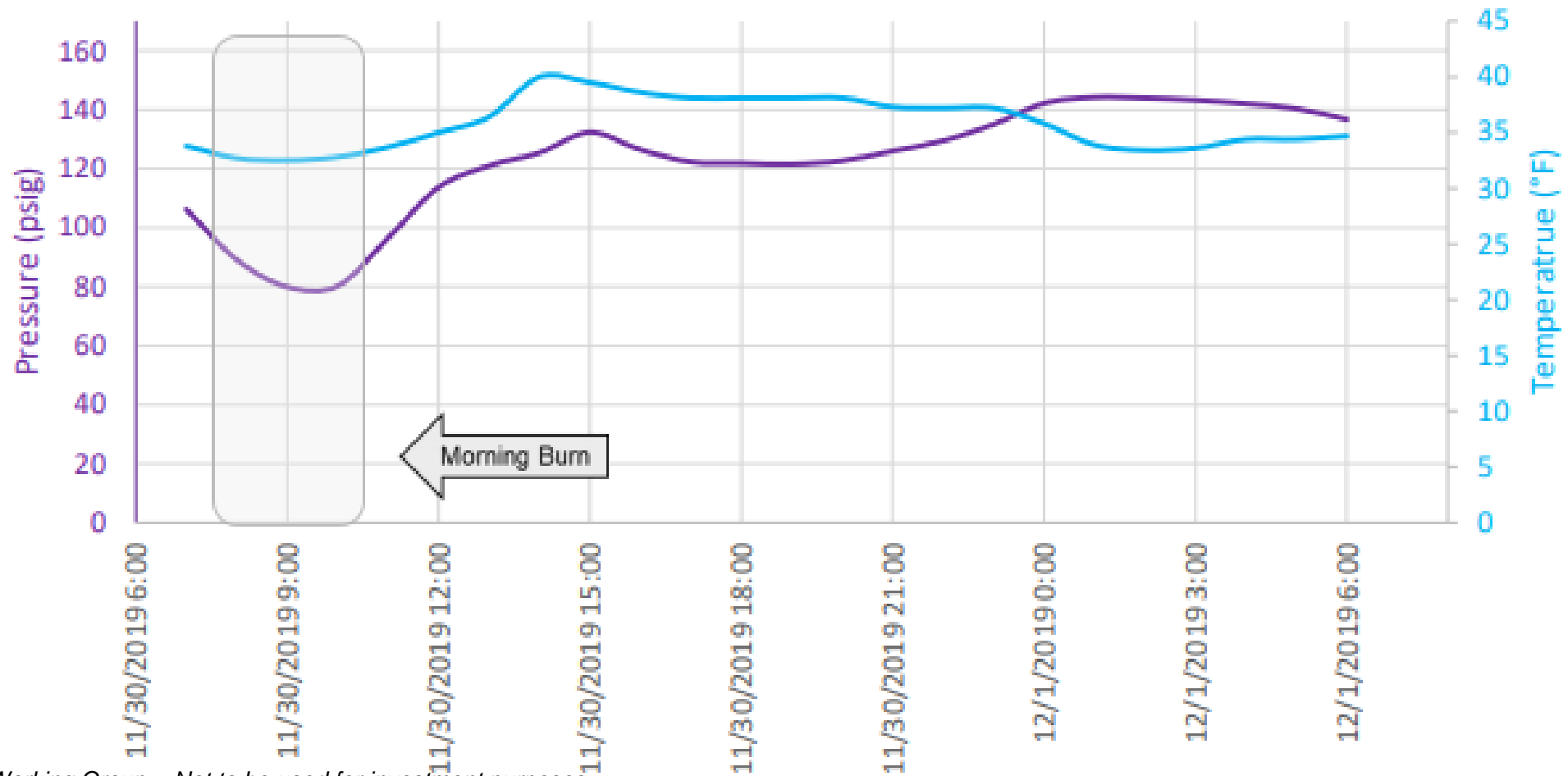
Distribution System Planning and Peak-Hour Planning Standard

Integrated Resource Planning (IRP) Process



Peak Hour – Typically in the Morning

Cannon Beach District Regulator Measurements



High Level Summary of Distribution Resource Planning Standards

Distribution Resource Planning Standard

Peak-Hour Standard (current status)

- Monitor the current system with modeling to identify areas of concern
- Use pressure recording devices (e.g. electronic portable pressure recorder (EPPR)) to observe and validate pressure criteria violations
- If pressure criteria violations are observed develop a solution with appropriate alternatives analysis

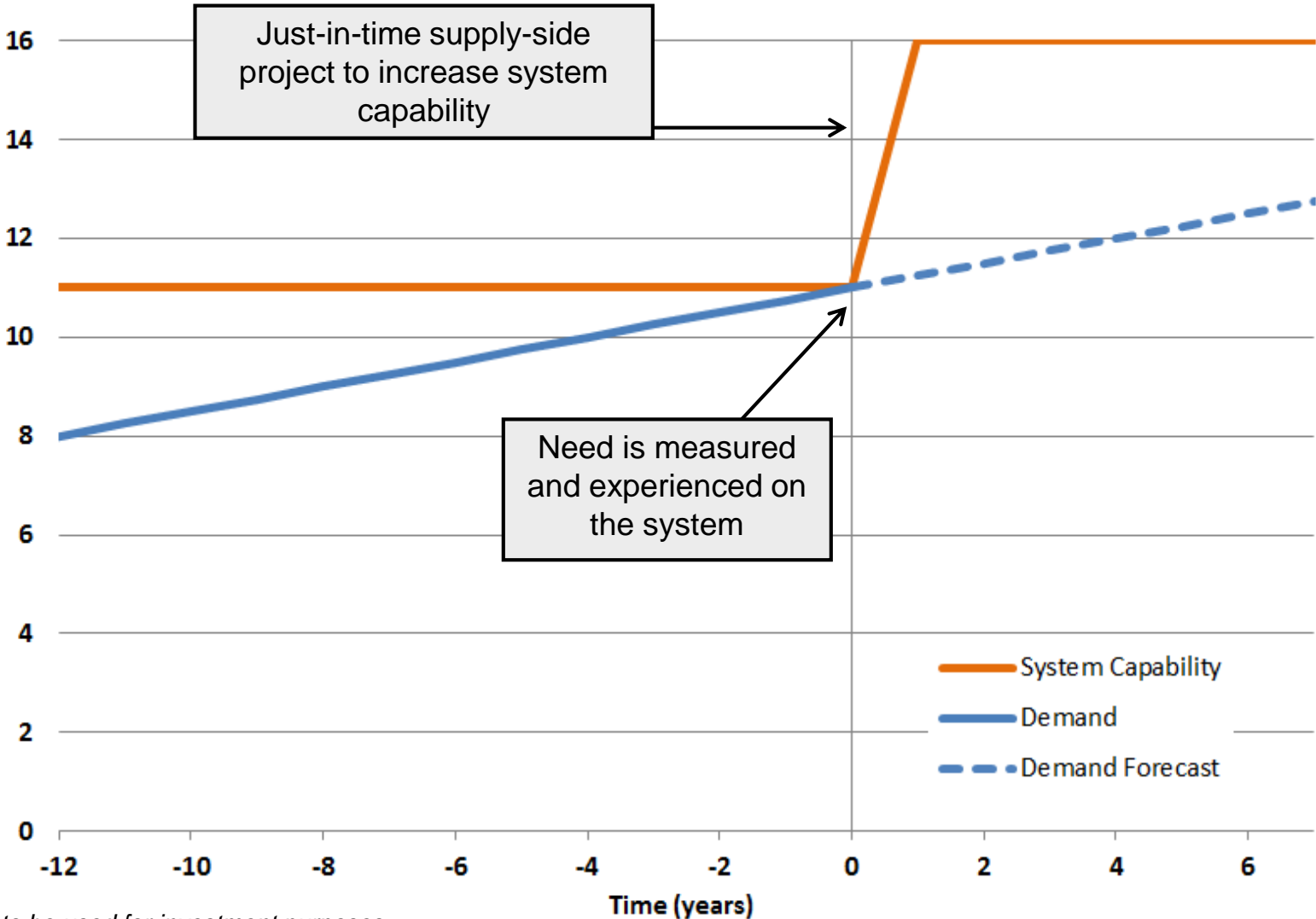
This current standard provides just-in-time solutions, with risks and shortcomings that we want to address.

NW Natural is looking to improve the distribution system planning process to be able to implement a forward-looking planning standard



Current Distribution System Planning: Just-in-Time Solutions

Simple Model



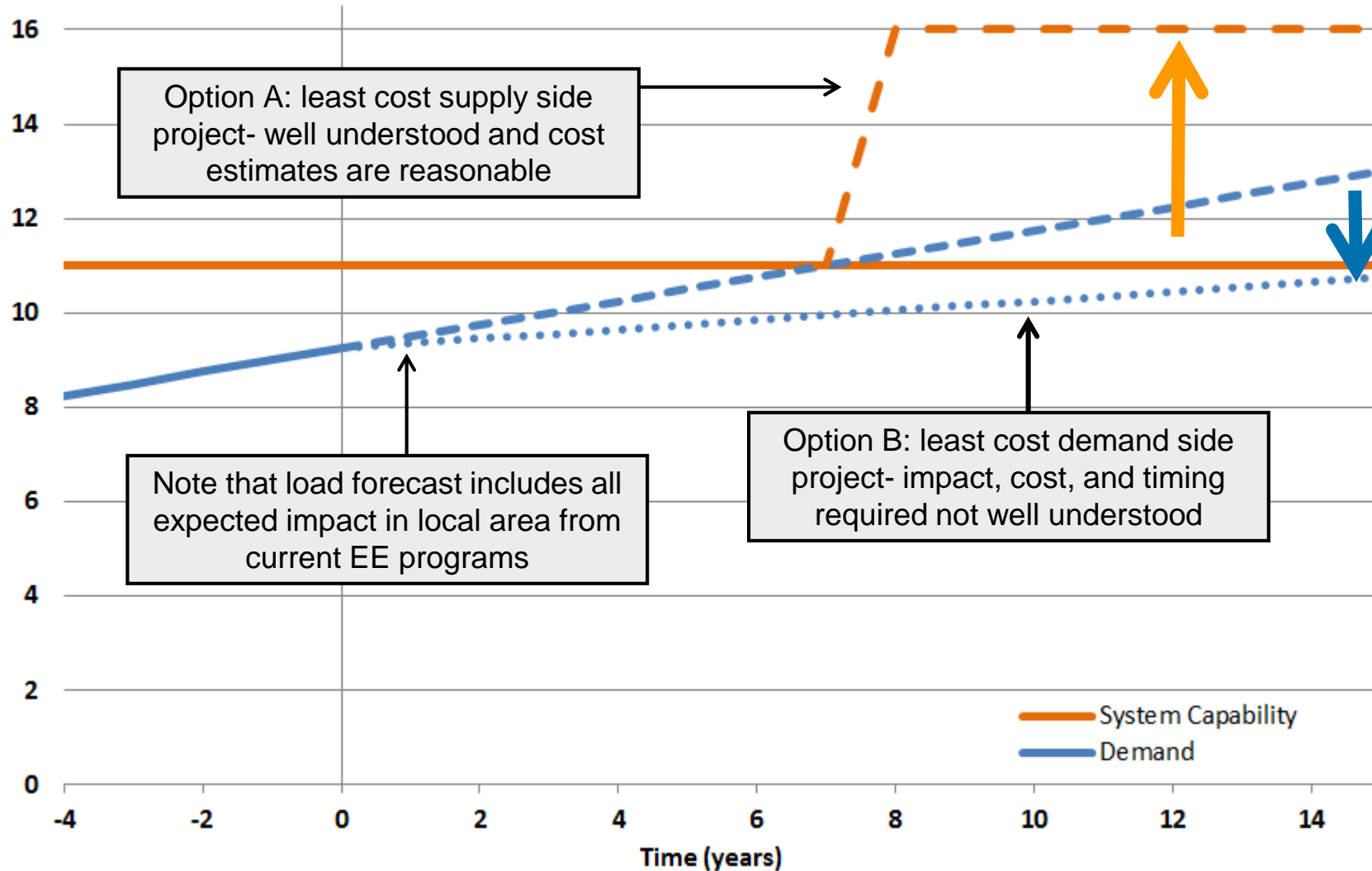
NW Natural is Improving Our Distribution System Planning Process

NW Natural is working on a forward-looking process that forecasts the need for distribution system projects in advance of the system becoming constrained

- A forward-looking process is necessary to be able to implement various demand-side options on other non-pipeline solutions, which may require longer lead times
- Additionally a forward-looking process will fundamentally rely on a forecasted peak demand, which would not have any observed pressure violations
- The goal would be to develop a peak-hour forecast for a specific location
- Future TWGs will work with stakeholders to establish the appropriate planning standard needed for this forward-looking process

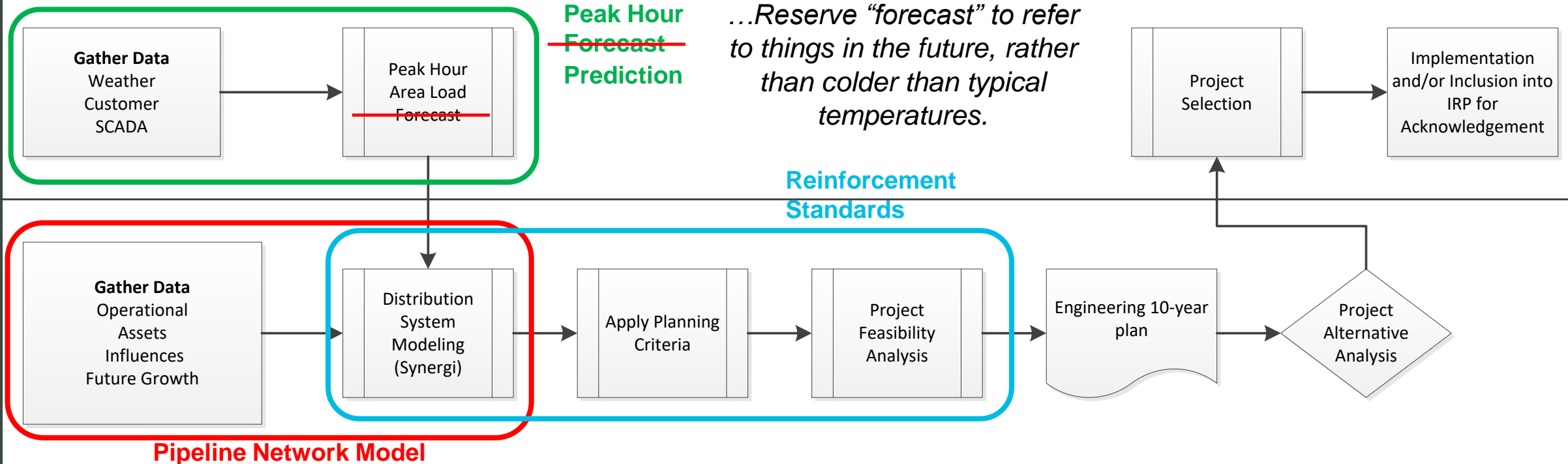
Road Ahead: Forward-Looking Distribution System Planning

Simple Model



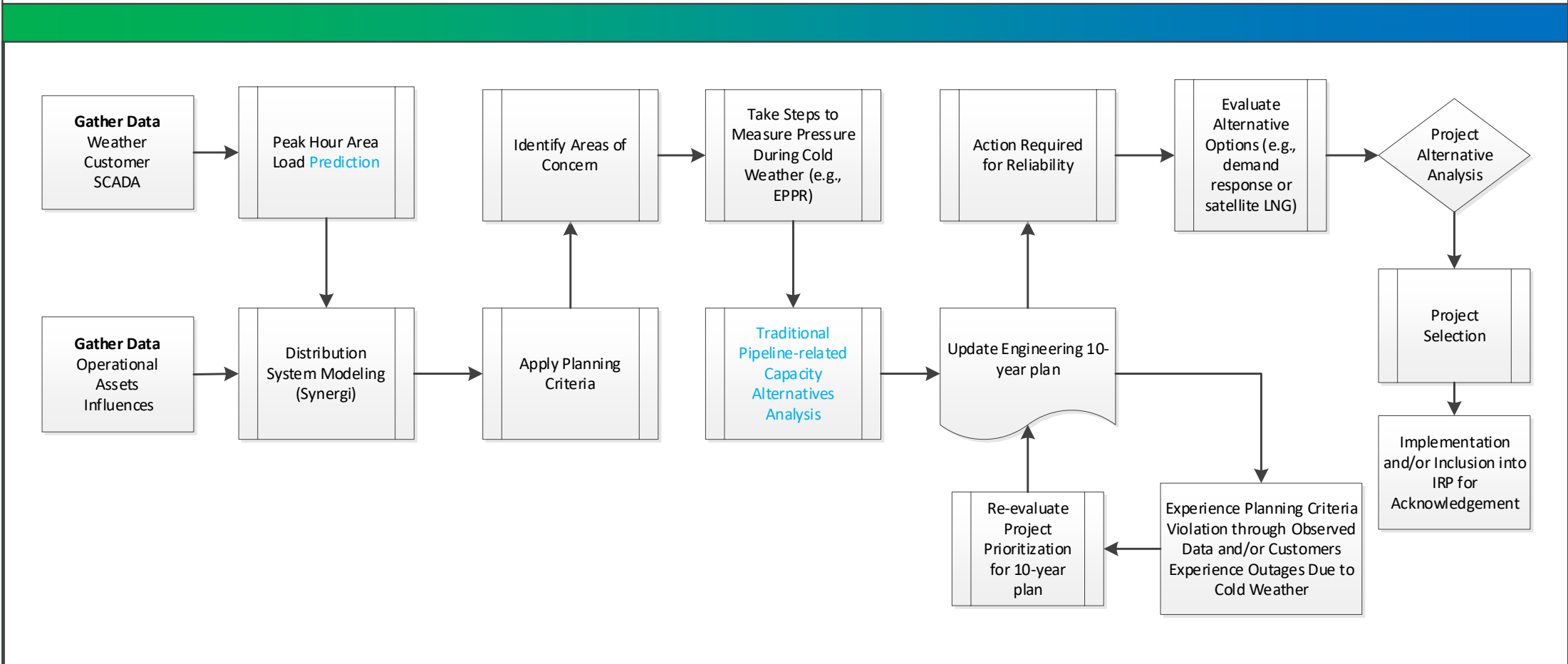
Distribution System Planning Process Presented in the 2018 IRP

Long Term Distribution System Planning Process



Updated Distribution System Planning Process: Just-in-Time Solutions

Long Term Distribution System Planning Process



What it Will Take to Improve the Process:

Hurdles to Current Implementation:

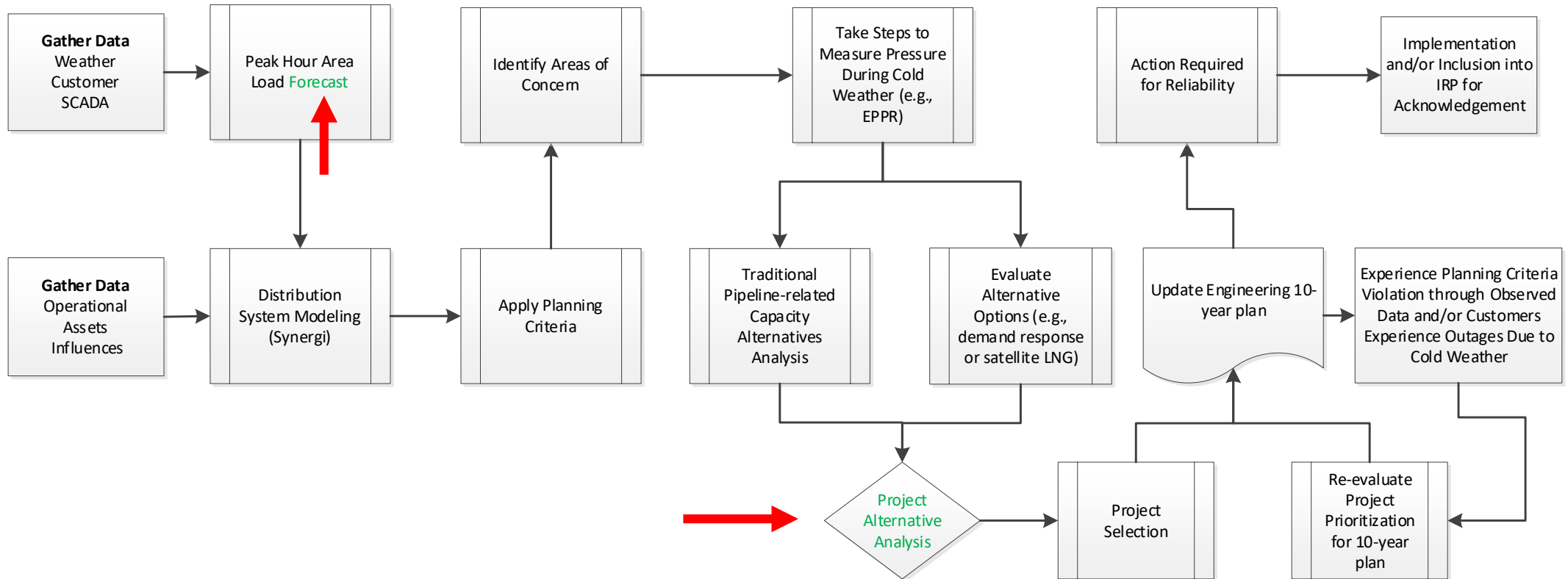
- Isolating specific areas of the system for forecasting
- Implementing forward-looking forecasts within Synergi model

Synergi Pipeline Modeling Improvement Project - CMM (Customer Management Module):

- Will allow area-specific forecasts for the future
- Based on customer-specific data within areas of interest

Road Ahead: Forward-Looking Distribution System Planning Process

Long Term Distribution System Planning Process – Forward Looking



Distribution System Planning Options

Distribution System Planning Alternatives (not all options are possible or applicable in all situations)			Option Currently Considered for Cost-Effectiveness Evaluation	
Supply-Side Alternatives	Pipeline Related Capacity Options	Loop existing pipeline	✓	
		Replace existing pipeline	✓	
		Install pipeline from different source location into area	✓	
		Upgrade existing pipeline infrastructure	✓	
		Add or upgrade regulator to serve area of weakness	✓	
		Gate station upgrades	✓	
		Add compression to increase capacity of existing pipelines	✓	
	Non-Pipeline Solutions	Distributed Energy Resources (DER)	Mobile/fixed geographically targeted CNG storage	✓
			Mobile/fixed geographically targeted LNG storage	✓
			On-system gas supply (e.g. renewable natural gas, H2)	✓
Geographically targeted underground storage			✓	
Demand-Side Alternatives	Demand Response	Interruptible schedules (DR by rate design)	✓	
		Geographically targeted interruptibility agreements	✓	
		Geographically targeted demand response (GeoDR)		
	Energy Efficiency	Peak hour savings from normal statewide EE programs	✓	
		Geographically targeted energy efficiency (GeoTEE)		

Questions?

Strategic Planning | Integrated Resource Planning Team
irp@nwnatural.com