Q. HOW WAS YOUR TARGET RESERVE OF $6.55 MILLION DEVELOPED?

A. As indicated above, I ran a Monte Carlo simulation on the loss history of CenterPoint Houston. From the 5,000 iterations of simulated experience, I was able to determine that in any 25-year period, the largest annual expected impact on the self-insurance reserve is approximately $6.55 million.

Q. WHY IS THIS RESERVE LEVEL APPROPRIATE?

A. This reserve level is the amount that should be carried by CenterPoint Houston to make an actuarially sound provision for coverage of the self-insured losses. The target reserve will be sufficient if annual losses are equal to or less than the target in a given year provided the reserve is already in place at its target amount; but if the actual losses exceed the amount accrued for the expected annual amount for several years in a row, the self-insurance reserve may be depleted.

For example, once the reserve level has been reached, if there are several years with losses of approximately $4 million, then the reserve balance will remain relatively stable. However, if there are two consecutive years with annual aggregate losses of more than $8 million each year, the self-insurance reserve would be in a deficit position. The deficit amount would need to be collected from future ratepayers.

Q. DOES THE PRESENCE OF A RESERVE OR ACCRUAL DESIGNED TO REACH A TARGET LEVEL ENSURE THAT THE RESERVE BALANCE WILL BE ADEQUATE TO COVER EVERY PROPERTY LOSS?

A. No. As explained above, once the reserve reaches its targeted level, on average it should cover typical annual losses, but should also be enough to cover a once in 25-year event. Larger loss events are possible, and should one occur, the reserve would not cover the full amount. Those events are much less common and therefore, I recommended that CenterPoint Houston not consider those events in establishing the target level for the reserve balance.

Q. WHAT IS THE BALANCE OF THE RESERVE?

A. As shown on Rate Filing Package Schedule II-B-7, page 1 of 2, the adjusted balance of the reserve is a deficit balance of approximately ($5.791 million) as of December 31, 2018.

Q. WHAT ARE THE INDIVIDUAL COMPONENTS OF THE ANNUAL ACCRUAL TO THE SELF-INSURANCE RESERVE INDICATED BY YOUR ANALYSIS?

A. The annual amount to be accrued each year is $7.685 million, which is composed of two elements. First, there is $3.575 million each year to provide for the year's annual expected covered losses from property loss event damages. Second, there should be an accrual of $4.11 million each year for three years to provide for the variation in annual losses from year to year by building the total self-insurance reserve from the test year balance of approximately ($5.791 million) up to the $6.55

million level. I have recommended a three-year period to balance the interests of future ratepayers versus past ratepayers.

Q. ARE THESE CALCULATIONS PREPARED IN ACCORDANCE WITH GENERALLY ACCEPTED ACTUARIAL PROCEDURES?

A. Yes. The process reflects generally accepted actuarial procedures. However, I have made certain adjustments to reflect the nature of ratemaking for public utilities. For example, it would be customary to project losses to the anticipated cost level of the future time period during which rates will be in effect. Because of the historical test year approach to utility ratemaking and the adjustment of expense items based on known and measurable quantities only, I have limited loss adjustments to the cost levels. The dates to which the losses were adjusted reflect the dates of the most recent indices available at the time the adjustments were made. On the other hand, common actuarial practice would be to project the cost of expected losses to the future period when they will be incurred, a level that would be greater than the level recommended in my testimony.

In addition, no adjustment has been made to reflect future increased exposure to loss. For example, in 2019 CenterPoint Houston may own more property in the service area that is exposed to loss than it had in years prior to 2018. This would increase the exposure to loss, and lead to a higher recommended reserve.

Q. HOW WILL THE SELF-INSURANCE RESERVE ACCRUALS OPERATE?

A. The excess of annual expected losses over actual self-insured losses, to the extent there is any such excess, will accrue to the self-insurance target reserve and cause

CenterPoint Houston to reach its target earlier, all other things being equal. Any deficiency between the annual expected losses and the actual self-insured layer losses in any calendar year will serve to extend the period over which the Company can expect to reach its target.

VI. COST BENEFIT ANALYSIS

Q. HOW DID YOU DETERMINE THAT SELF-INSURANCE IS A LOWER COST ALTERNATIVE FOR THOSE T&D PROPERTY LOSSES GREATER THAN $100,000?

A. There are at least two ways to consider the cost-benefit of self-insuring these losses. The first is by considering the manner in which insurance companies set premiums and the second is by an actual comparison of the recommended self-insurance accrual to the estimated insurance premium for comparable coverage, if available.

Q. WHAT ASPECTS OF AN INSURANCE COMPANY'S PREMIUM DETERMINATION PROCESS DID YOU CONSIDER IN CONCLUDING THAT THE SELF-INSURANCE APPROACH FOR THE DESIGNATED LAYER OF LOSSES IS APPROPRIATE?

A. Insurance companies include provisions in their premiums for all costs associated with the transfer of the insurance risk. Hence, they include provisions for losses, loss adjustment expenses, non-loss related expenses, premium taxes, and a profit.

A self-insurance reserve, such as CenterPoint Houston's reserve, does not need to include many of the provisions other than those for losses and loss-related expenses. For example, a self-insurance reserve does not need to pay premium taxes and other state-imposed fees. An insurance company needs to make a profit on the business it transacts. A self-insurance reserve, on the other hand, is not intended to generate a profit and, hence, no provision for profit needs to be included in the accrual provisions. Insurance companies also incur costs associated with the acquisition of insured risks. The largest of these expenses is that associated with the payment of commissions to insurance agents or brokers to place the business. A self-insurance reserve does not include any provision for commissions because there are no insurance agents or brokers involved. Finally, an insurance company must expend resources to underwrite risks, market its products, and maintain overhead expenses. A self-insurance reserve does not need to provide for these costs.

In summary, self-insurance saves the costs of premium taxes, commissions, profit, and many of the general expenses associated with the operation of an insurance company.

Q. WHAT OTHER COST BENEFIT ANALYSIS HAVE YOU RELIED UPON TO SHOW THAT THE COST FOR THE SELF-INSURED LAYER IS LOWER THAN THE COST OF PURCHASING INSURANCE FOR THE SAME LAYER OF INSURANCE AND IS IN THE INTEREST OF THE COMPANY'S CUSTOMERS?

A. Comparing the cost of self-insurance versus the cost of purchasing insurance establishes that it is more cost effective for CenterPoint Houston to self-insure. As discussed in the testimony of Company witness Robert B. McRae, CenterPoint Houston's risk manager has tried to obtain coverage for T&D assets damaged by storms. The risk manager has been unable to find coverage at any cost reasonably close to the cost of self-insurance. This is due to the extensive damage caused by hurricanes to electric utilities across the country in the past several years.

VII. CONCLUSION

Q. WHAT DO YOU CONCLUDE REGARDING CENTERPOINT HOUSTON'S REQUEST FOR SELF-INSURANCE RESERVE TO COVER T&D PROPERTY LOSSES?

A. I have conducted an analysis that meets the Commission's rule requirements and have demonstrated that self-insurance is necessary and desirable given the lack of reasonably priced commercial insurance. I have determined that a target reserve of $6.55 million is reasonable, and the amount is in fact less than the amount previously approved for CenterPoint Houston by the Commission. I have also determined that an annual accrual of $7.685 million, which is comprised of amounts intended to cover expected property losses and to build up the reserve balance from its current deficit level to a target balance of $6.55 million, is reasonable.

Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes, at this time.

STATE OF TEXAS §

COUNTY OF COLLIN **§**
§

AFFIDAVIT OF GREGORY S. WILSON

BEFORE ME, the undersigned authority, on this day personally appeared Gregory S. Wilson who having been placed under oath by me did depose as follows:

1. "My name is Gregory S. Wilson. I am of sound mind and capable of making this affidavit. The facts stated herein are true and correct based upon my personal knowledge.

2. I have prepared the foregoing Direct Testimony and the information contained in this document is true and correct to the best of my knowledge."

Further affiant sayeth not.

Gregory S. Wilson

SUBSCRIBED AND SWORN TO BEFORE ME on this 18TH day of March, 2019.

NOTARY PUBLIC
STATE OF TEXAS
DEBRA WEBB
Notary ID # 853801
My Commission Expires
November 26, 2020

Debra Webb
Notary Public in and for the State of TEXAS

My commission expires: 11-26-20

GREGORY S. WILSON, FCAS, MAAA
Vice President and Principal

CURRENT POSITION

Mr. Wilson is a Vice President and Principal with Lewis & Ellis, Inc.

EXPERIENCE:

Mr. Wilson's responsibilities include evaluating the adequacy of insurance company reserve levels in conjunction with actuarial certification for the annual statement as well as state insurance department examinations. He also evaluates the adequacy of loss reserves for several self-insured companies. In addition, he performs rate level analyses for insurance companies and helps them prepare filings for the state insurance departments, as well as self-insured analyses for electric utilities and prepares testimony for the Public Utility Commission.

Prior to joining the firm, Mr. Wilson was a Principal Consultant at PricewaterhouseCoopers LLP. His responsibilities were similar to his current responsibilities. In addition, he reviewed retrospective rating calculations for several companies involved in class action litigation in Texas. He also performed several funding analyses for governmental entities.

Prior to joining PricewaterhouseCoopers LLP, Mr. Wilson was Vice President of Amica Mutual Insurance Company in Providence, Rhode Island.

There, he supervised all aspects of ratemaking, from procedures to recommendations, helped negotiate the purchase of reinsurance, determined IBNR, developed a strategy for Massachusetts Automobile and developed other states' residual market strategies, in particular, New York and New Jersey.

EDUCATION

Mr. Wilson received his Bachelor's degree in Applied Mathematics from the University of Rhode Island.

PROFESSIONAL ACTIVITIES

Mr. Wilson is a former member of the Casualty Actuarial Society's Examination Committee, Committee on Ratemaking, and Committee on Reserving. He is also a Past President of the Southwest Actuarial Forum.

CenterPoint Houston
Calculation of Recommended Accrual

Expected Annual Loss	3,575,000
Incremental Amount to Build Reserve	4,110,000
Total Annual Accrual	7,685,000

CenterPoint Houston
Major Property Damage
Adjusted to Current Cost Levels
2005-2018

Year	Actual Loss	Trended Loss
2005	1,415,908	2,583,663
2006	805,440	1,275,173
2007	305,571	459,273
2008	1,328,357	1,757,035
2009	592,095	750,638
2010	324,737	400,833
2011	1,753,826	2,069,487
2012	2,956,001	3,408,047
2013	1,249,595	1,392,806
2014	4,603,359	4,955,928
2015	10,466,325	11,008,207
2016	7,551,754	7,847,737
2017	4,407,257	4,434,574
2018	8,971,199	8,971,198
Total	46,731,424	51,314,599

CenterPoint Houston
Example of Loss Trending Methodology

1)	Date of Loss	29-Mar-17
2)	Amount of Loss	$572,264
3)	Handy-Whitman Index - Electric Utility Construction South Central Region - Distribution Plant	
	a) January, 2017	672
	b) July, 2017	684
	c) March 29, 2017	677.768
	d) January, 2019	684
4)	Trend Factor (3d) / (3c)	1.009
5)	Cost-Adjusted Losses (2) x (4)	$577,414

GREGORY S. WILSON WORKPAPERS:

- WP GSW-1 Calculation.pdf
- WP GSW-2 Storm List.pdf
- WP GSW-2 Storm List.xlsx
- WP GSW-3 T&D Insurance.pdf

Date of Storm/Index	Trans. & Dist. Gross Loss	Handy-Whitman Index	Interpolated Index	Trend Factor	Trended Loss	Semi-Annual Total	Annual Total	Natural Log
01/01/05		368						
05/09/05	775,775		374.365	1 827	1,417,341			14.1642928
05/31/05	640,133		375.459	1.822	1,166,322			13.9693658
07/01/05		377				2,583,663		
01/01/06		401				0	2,583,663	
05/15/06	236,478		416.547	1.642	388,297			12.8695255
07/01/06		422				388,297		
08/15/06	183,400		429.092	1.594	292,339			12 5856698
11/15/06	385,562		443.592	1.542	594,537			13.2955387
01/01/07		451				886,876	1,275,173	
04/01/07	305,571		454.978	1.503	459,273			13.0374011
07/01/07		459				459,273		
01/01/08		521				0	459,273	
06/19/08	202,295		514.462	1.330	269,052			12.5026612
06/22/08	158,097		514 346	1.330	210,269			12.256143
07/01/08		514				479,321		
08/05/08	967,965		517 995	1.320	1,277,714			14.0605829
01/01/09		535				1,277,714	1,757,035	
04/19/09	136,581		527.243	1 297	177,146			12.084727
07/01/09		522				177,146		
12/25/09	455,514		543.163	1 259	573,492			13.259499
01/01/10		544				573,492	750,638	
06/08/10	156,304		551.856	1.239	193,661			12.1738657
07/01/10		553				193,661		
08/23/10	168,432		555.880	1.230	207,172			12.2413031
01/01/11		563				207,172	400,833	
06/05/11	112,954		575.845	1.188	134,190			11 8070112
07/01/11		578				134,190		
08/24/11	249,510		579.174	1.181	294,671			12 5936164
09/03/11	262,777		579.391	1.181	310,340			12.6454234
09/29/11	446,839		579.957	1.179	526,823			13.1746203
10/09/11	524,470		580.174	1.179	618,350			13.3348097
11/15/11	157,275		580.978	1.177	185,113			12.1287198
01/01/12		582				1,935,297	2,069,487	
04/16/12	109,985		587.824	1.164	128,023			11.7599639
01/09/12	270,511		582.440	1.174	317,579			12.668483
02/18/12	280,982		584 637	1.170	328,748			12.703048
03/20/12	214,219		586 341	1.167	249,994			12.4291917
04/20/12	457,142		588.044	1.163	531,656			13.1837511
06/16/12	595,236		591 176	1.157	688,688			13.4425441
07/01/12		592				2,244,688		
08/18/12	178,359		595.913	1.148	204,756			12.2295756
12/20/12	291,352		606.022	1.129	328,936			12.7036191
12/25/12	558,216		606.429	1.128	629,667			13.352947
01/01/13		607				1,163,359	3,408,047	
04/27/13	399,709		612.768	1.116	446,075			13.0082432
05/10/13	210,471		613.414	1.115	234,675			12.3659563
07/01/13		616				680,750		
10/27/13	481,036		623.054	1.098	528,178			13.1771881
10/31/13	158,379		589.293	1.161	183,878			12.1220278
01/01/14		627				712,056	1,392,806	
03/04/14	242,388		629.398	1.087	263,475			12.4817156
05/12/14	537,846		632.066	1.082	581,950			13.2741393
05/26/14	134,207		632.608	1.081	145,078			11.8850289
05/27/14	708,232		632.646	1.081	765,599			13.5484132
05/28/14	321,687		632.685	1 081	347,744			12.7592221
07/01/14		634				2,103,846		
07/03/14	189,557		634.163	1.079	204,532			12.2284793
08/11/14	1,206,606		637.342	1.073	1,294,689			14.0737808
07/04/14	318,728		634.245	1.078	343,589			12.7472009
07/31/14	317,050		636.446	1 075	340,828			12.7391343
10/02/14	184,496		641.582	1.066	196,673			12.1892954
10/06/14	442,562		641.908	1.066	471,771			13 0642488
01/01/15		649				2,852,082	4,955,928	
04/16/15	360,361		649.000	1.054	379,821			12 8474553
04/17/15	1,625,432		649.000	1 054	1,713,206			14.3538769

Date of Storm/Index	Trans. & Dist. Gross Loss	Handy-Whitman Index	Interpolated Index	Trend Factor	Trended Loss	Semi-Annual Total	Annual Total	Natural Log
04/25/15	449,119		649.000	1.054	473,372			13.0676359
04/26/15	759,939		649.000	1.054	800,976			13.5935865
05/14/15	106,161		649.000	1.054	111,893			11.625301
05/17/15	158,581		649.000	1.054	167,145			12.0266161
05/24/15	348,703		649.000	1.054	367,533			12.8145694
05/25/15	2,379,446		649.000	1.054	2,507,936			14.7349707
05/30/15	476,656		649 000	1.054	502,396			13.1271432
06/16/15	424,278		649.000	1.054	447,189			13.0107365
06/30/15	237,015		649 000	1.054	249,814			12.4284701
07/01/15		649				7,721,281		
08/11/15	923,053		651.005	1.051	970,129			13.7851841
08/19/15	126,032		651.397	1.050	132,333			11.7930795
08/25/15	268,189		651.690	1.050	281,598			12.5482356
10/24/15	882,482		654 625	1.045	922,193			13.7345102
10/31/15	473,227		654.967	1.044	494,049			13.1103904
12/13/15	268,398		657.071	1 041	279,402			12.5404075
12/27/15	199,252		657.755	1.040	207,222			12.2415442
01/01/16		658				3,286,926	11,008,207	
02/23/16	239,139		658.000	1.040	248,705			12.4240219
03/09/16	332,026		658.000	1.040	345,307			12.7521882
03/24/16	116,851		658.000	1.040	121,525			11.7078715
04/13/16	202,826		658.000	1 040	210,939			12.2593248
04/17/16	1,897,917		658.000	1.040	1,973,834			14.4954883
04/27/16	585,133		658.000	1.040	608,538			13.3188145
05/09/16	376,414		658.000	1.040	391,470			12.8776647
05/14/16	343,950		658.000	1 040	357,708			12.787471
05/21/16	385,456		658.000	1.040	400,874			12.9014036
05/25/16	1,325,646		658.000	1.040	1,378,672			14 1366314
06/01/16	303,792		658.000	1.040	315,944			12.6633208
06/12/16	341,194		658.000	1.040	354,842			12.7794269
06/18/16	164,069		658.000	1.040	170,632			12.0472617
06/28/16	273,999		658.000	1.040	284,959			12.5601005
07/01/16		658				7,163,949		
07/25/16	123,853		659.826	1 037	128,436			11.7631848
08/13/16	362,280		661.272	1.034	374,597			12.8336066
12/17/16	177,211		670.859	1.020	180,755			12.1048964
01/01/17		672				683,788	7,847,737	
01/02/17	200,051		672.066	1.018	203,652			12.224168
01/22/17	510,899		673.392	1.016	519,074			13.1598015
02/14/17	302,014		674.917	1.013	305,940			12.6311439
03/24/17	312,450		677.436	1 010	315,575			12.6621516
03/29/17	572,264		677.768	1.009	577,414			13.2663155
05/22/17	206,892		681.348	1.004	207,719			12.2439433
05/23/17	424,705		681.414	1 004	426,404			12 963142
06/04/17	271,005		682.210	1.003	271,818			12.5128863
07/01/17		684				2,827,596		
07/09/17	434,610		684.000	1.000	434,610			12.982204
07/15/17	498,900		684.000	1.000	498,900			13.1201611
08/07/17	337,294		684.000	1.000	337,294			12 72871
10/20/17	111,600		684.000	1 000	111,600			11.6226732
10/22/17	224,574		684.000	1 000	224,574			12.3219597
01/01/18		684				1,606,978	4,434,574	
01/11/18	328,474		684 000	1 000	328,474			12.7022118
01/16/18	699,962		684.000	1.000	699,962			13.458782
03/28/18	579,736		684.000	1.000	579,736			13.2703284
04/03/18	251,005		684.000	1.000	251,005			12 4332294
04/14/18	272,649		684.000	1.000	272,649			12.5159388
04/22/18	109,390		684.000	1.000	109,390			11.6026789
05/20/18	538,475		684.000	1.000	538,475			13.1964969
05/26/18	592,233		684.000	1.000	592,233			13.2916562
07/01/18		684				3,371,924		
06/03/18	461,623		684.000	1.000	461,623			13.0425046
06/14/18	108,478		684.000	1.000	108,478			11.5943046
06/20/18	125,961		684.000	1.000	125,961			11.7437239
07/03/18	296,102		684 000	1.000	296,102			12 5984607
07/09/18	699,682		684.000	1 000	699,682			13.4583809

Date of Storm/Index	Trans. & Dist. Gross Loss	Handy-Whitman Index	Interpolated Index	Trend Factor	Trended Loss	Semi-Annual Total	Annual Total	Natural Log
07/12/18	184,656		684.000	1.000	184,656			12.1262519
08/08/18	155,060		684.000	1.000	155,060			11.9515692
08/09/18	140,099		684.000	1.000	140,099			11.8501018
08/10/18	181,575		684.000	1.000	181,575			12.1094258
08/21/18	256,044		684.000	1.000	256,044			12.453106
09/03/18	250,629		684.000	1.000	250,629			12.4317273
09/09/18	346,943		684.000	1.000	346,943			12.756915
09/22/18	187,205		684.000	1.000	187,205			12.1399615
09/29/18	166,858		684.000	1.000	166,858			12.024899
10/15/18	110,993		684.000	1.000	110,993			11.61722
10/31/18	954,264		684.000	1.000	954,264			13.7686952
11/12/18	137,006		684.000	1.000	137,006			11.8277794
12/07/18	420,432		684.000	1.000	420,432			12 9490374
12/20/18	245,787		684.000	1.000	245,787			12.4122209
12/26/18	169,877		684.000	1.000	169,877			12.0428276
01/01/19		684				5,599,274	8,971,198	
Total	46,731,424						51,314,599	
Average							3,801,081	

Total Number of Claims	119
Number of Years	14.0
Average per year	8.500

CenterPoint Energy Houston Electric
Storm List 2005-2018
O&M by Storm

Year	Date of Storm			Total O&M
2005	5/9/2005			$775,774.77
2005	5/31/2005			$640,132.85
2005	9/24/2005			$27,429,922.00
2006	5/15/2006			$236,477.77
2006	8/15/2006			$183,399.71
2006	11/15/2006			$385,562.43
2007	4/1/2007			$305,571.16
2008	6/19/2008			$202,295.26
2008	6/22/2008			$158,097.43
2008	8/5/2008			$967,964.97
2009	4/19/2009			$136,581.49
2009	12/24/2009			$455,513.76
2010	6/8/2010			$156,304.46
2010	8/23/2010			$168,432.26
2011	6/5/2011			$112,954.46
2011	8/24/2011			$249,510.14
2011	9/3/2011			$262,777.22
2011	9/29/2011			$446,839.02
2011	10/9/2011			$524,469.77
2011	11/15/2011			$157,274.98
2012	4/16/2012			$109,985.25
2012	1/9/2012			$270,510.51
2012	2/18/2012			$280,981.55
2012	3/20/2012			$214,219.26
2012	4/20/2012			$457,141.50
2012	6/16/2012			$595,236.24
2012	8/18/2012			$178,359.11
2012	7/12/2012			$4,510.40
2012	12/20/2012			$291,351.81
2012	12/25/2012			$558,215.79
2013	4/27/2013			$399,709.11
2013	5/10/2013			$210,470.74
2013	10/27/2013			$481,036.16
2013	10/31/2013			$158,378.99
2014	3/4/2014			$242,387.75
2014	4/14/2014			$17,632.48
2014	5/12/2014			$537,846.28

CenterPoint Energy Houston Electric
Storm List 2005-2018
O&M by Storm

Year	Date of Storm			Total O&M
2014	5/26/2014			$134,207.49
2014	5/27/2014			$708,231.78
2014	5/28/2014			$321,687.41
2014	7/3/2014			$189,556.92
2014	8/11/2014			$1,206,606.41
2014	7/4/2014			$318,728.01
2014	7/31/2014			$317,049.63
2014	10/2/2014			$184,495.81
2014	10/6/2014			$442,561.85
2015	4/16/2015			$360,361.46
2015	4/17/2015			$1,625,432.43
2015	4/25/2015			$449,119.13
2015	4/26/2015			$759,939.46
2015	5/13/2015			$82,371.97
2015	5/14/2015			$106,160.62
2015	5/17/2015			$158,581.46
2015	5/21/2015			$62,076.34
2015	5/24/2015			$348,703.39
2015	5/25/2015			$2,379,445.98
2015	5/30/2015			$476,656.18
2015	6/16/2015			$424,277.95
2015	6/30/2015			$237,014.74
2015	8/11/2015			$923,053.08
2015	8/19/2015			$126,031.78
2015	8/25/2015			$268,188.52
2015	10/24/2015			$882,481.70
2015	10/31/2015			$473,227.22
2015	12/13/2015			$268,397.87
2015	12/27/2015			$199,251.57
2016	2/23/2016			$239,139.22
2016	3/9/2016			$332,025.66
2016	3/24/2016			$116,850.52
2016	4/13/2016			$202,826.06
2016	4/17/2016			$1,897,917.02
2016	4/27/2016			$585,132.63
2016	5/9/2016			$376,413.66
2016	5/14/2016			$343,949.56

CenterPoint Energy Houston Electric
Storm List 2005-2018
O&M by Storm

Year	Date of Storm			Total O&M
2016	5/21/2016			$385,456.20
2016	5/25/2016			$1,325,646.32
2016	6/1/2016			$303,792.46
2016	6/12/2016			$341,193.88
2016	6/18/2016			$164,068.78
2016	6/28/2016			$273,999.01
2016	7/25/2016			$123,853.27
2016	8/13/2016			$362,279.68
2016	12/17/2016			$177,210.53
2017	1/2/2017			$200,051.09
2017	1/22/2017			$510,899.48
2017	2/14/2017			$302,013.71
2017	3/24/2017			$312,450.49
2017	3/29/2017			$572,264.03
2017	5/22/2017			$206,891.80
2017	5/23/2017			$424,704.94
2017	6/4/2017			$271,004.53
2017	7/9/2017			$434,609.86
2017	7/15/2017			$498,900.05
2017	7/22/2017			$98,080.38
2017	8/7/2017			$337,293.91
2017	8/25/2017			$62,959,581.44
2017	10/20/2017			$111,599.65
2017	10/22/2017			$224,573.81
2018	1/11/2018			$328,473.63
2018	1/16/2018			$699,962.45
2018	3/28/2018			$579,736.16
2018	4/3/2018			$251,005.32
2018	4/14/2018			$272,648.54
2018	4/22/2018			$109,390.45
2018	5/20/2018			$538,475.29
2018	5/26/2018			$592,233.45
2018	6/3/2018			$461,623.37
2018	6/14/2018			$108,478.21
2018	6/20/2018			$125,960.53
2018	7/3/2018			$296,102.41
2018	7/9/2018			$699,681.76

CenterPoint Energy Houston Electric
Storm List 2005-2018
O&M by Storm

Year	Date of Storm			Total O&M
2018	7/12/2018			$184,656.36
2018	8/8/2018			$155,060.28
2018	8/9/2018			$140,098.61
2018	8/10/2018			$181,575.31
2018	8/21/2018			$256,044.36
2018	9/3/2018			$250,628.57
2018	9/9/2018			$346,942.73
2018	9/22/2018			$187,205.37
2018	9/29/2018			$166,858.10
2018	10/15/2018			$110,992.73
2018	10/31/2018			$954,263.57
2018	11/12/2018			$137,005.92
2018	12/7/2018			$420,431.74
2018	12/20/2018			$245,787.07
2018	12/26/2018			$169,876.60

$137,385,599.52

Jackson, Robert W.

From:	Jackson, Robert W.
Sent:	Wednesday, March 13, 2019 4:17 PM
To:	'GWilson@LewisEllis.com'
Cc:	Andrea Stover (andrea.stover@bakerbotts.com)
Subject:	CenterPoint Houston T&D Insurance Lack of Availability -- CONFIDENTIAL
Attachments:	T&D INSURANCE MARKET_UPDATE 030519.pptx

Greg:
Attached is the document which CenterPoint Houston's risk manager obtained, describing the lack of availability of electric transmission and distribution property insurance. Pending further instructions, please treat this information as Confidential.
Thanks.

CenterPoint. Energy
Robert W. Jackson
Manager of Regulatory Affairs | Regulatory Portfolio Management Organization
713.207.5584 w.
CenterPointEnergy.com

McGRIFF, SEIBELS & WILLIAMS, INC.

POWER MARKET UPDATE

INSURANCE BROKERAGE SERVICES

March 5th, 2019

McGRIFF, SEIBELS & WILLIAMS, INC.

CenterPoint. Energy

Other Miscellaneous

CenterPoint. Energy

Transmission and Distribution Lines

- There continues to be no viable market place for meaningful T&D coverage
  - Insurance companies do not have reinsurance to protect them so explicitly exclude the coverage on property policies
  - A few syndicates in London may write small net lines but available capacity is minimal – maybe $20MM - $25MM excess of large retentions
  - No US markets will offer capacity
  - With rare exception insurance market in general consider T&D lines uninsurable
- AEGIS product that was being promoted in 2018 was not successful
  - MSW are aware of no utilities that purchased the product
  - Limited capacity (~$25MM), extremely high rate on line (15-20%) and large attachment points
  - Not meaningful protection for large highly exposed utility companies
- Parametric Products are available
  - Swiss Re and other Alternative Risk companies
  - Minimum dual trigger products (wind speed thresholds and geographic touch points = varying payout amounts)
  - Similar shortcomings to above (limited capacity and high rate on line type products)
  - East coast example: up to 25% rate on line for $10MM in occurrence limits
  - Max. payout achieved if wind field measured at specific locations exceed 90 mph
  - Allows for one reinstatement of the limit

APPLICATION OF CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC FOR AUTHORITY TO CHANGE RATES	**§ § §**	**PUBLIC UTILITY COMMISSION OF TEXAS**

DIRECT TESTIMONY

OF

DR. J. STUART MCMENAMIN

ON BEHALF OF

CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC

April 2019

TABLE OF CONTENTS

LIST OF EXHIBITS

EXECUTIVE SUMMARY OF J. STUART MCMENAMIN

My testimony explains how detailed data from the CenterPoint Energy advanced metering system is used to adjust daily and monthly energy usage and billing determinants in order to ensure that its rates are set on data that reflect normal weather, as contemplated by the Public Utility Commission's rate filing package instructions. The weather adjustment method used is reasonable and necessary when preparing rates. Specifically, I address:

- weather adjustment models for daily energy;
- weather adjustment models for class peaks and CP values;
- weather adjustment models for customer demand;
- calculation of normal weather;
- unadjusted test year load data;
- adjusted test year load data; and
- adjusted revenue month customer demand and billing demand.

Utilities make weather adjustments to ensure that rates are set to meet revenue requirements in a year with normal weather. By looking at weather data from recent years, we can construct a test year weather pattern that is representative of typical weather conditions. This insures that rates are not based upon the specific and possibly uncharacteristic weather pattern that occurred in one particular year. The weather adjustment methods summarized in my testimony are consistent with industry practice and the weather adjustment results provide accurate estimates of the impact of weather deviations from normal in 2018. Schedules related to the weather adjustment of energy, class peak, class coincident loads, and customer demand are attached to my testimony.

DIRECT TESTIMONY OF J. STUART MCMENAMIN

I. INTRODUCTION AND QUALIFICATIONS

Q. PLEASE STATE YOUR NAME, BUSINESS ADDRESS, AND PLACE OF EMPLOYMENT.

A. My name is John Stuart McMenamin. I am Director of Forecasting at Itron Inc. ("Itron"), 12348 High Bluff Drive, Suite 210, San Diego, CA 92130.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING?

A. I am testifying on behalf of CenterPoint Energy Houston Electric, LLC ("CenterPoint Houston" or "Company").

Q. PLEASE DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL EXPERIENCE.

A. I received my undergraduate degree in Mathematics and Economics from Occidental College in Los Angeles, California in 1971. My post graduate degree is a Ph.D. in Economics from the University of California, San Diego in 1976. I have worked in the fields of energy forecasting and load research since 1976 and have consulted with many of the major electric and gas utilities in North America. In the 1980's and early 1990's, my work focused on end-use modeling and I was the principal investigator for the Electric Power Research Institute end-use modeling programs. More recently, my work has focused on methods that combine econometric and end-use concepts. For the last 16 years, I have been employed by Itron, and I am currently Director of the Forecasting and Load Research Solutions group at Itron. Additional details are available in my resume, which is attached to this testimony as Exhibit JSM-1.

Q. PLEASE DESCRIBE YOUR DUTIES AS DIRECTOR OF FORECASTING AT ITRON.

A. For the last 15 years, I have been employed by Itron as Director of the Forecasting Solutions group. During this period, I have been in charge of development for our Automated Forecasting System which is used by many large system operators, like the California ISO, Midwest ISO, and ERCOT. Also, I am responsible for Itron products and services related to financial forecasting, including the Itron statistical package (MetrixND) which is used by utilities (like CenterPoint Houston, Oncor, CPS, TNMP, Xcel Energy, and Entergy) to forecast and analyze customers, sales, revenues, and hourly loads. In addition to product design and algorithm development, I direct or contribute to consulting projects related to forecasting and load research for utilities. For the last 10 years, I have been working with utilities in North America to help them improve analysis and forecasting processes using advanced metering system (AMS) data. The work that was conducted for CenterPoint Houston is an example of this type of work.

II. PURPOSE OF TESTIMONY

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY IN THIS PROCEEDING?

A. The purpose of my testimony is to present the methods and data that were used to develop weather adjustments for the Company's filing, including adjustments for monthly sales, customer demand, billing demand, class peaks, and class loads at the time of CenterPoint Houston and ERCOT peaks. The estimates were developed using AMS data for the CenterPoint Houston population of metered customers. My testimony describes the organization and processing of the 15-minute AMS data, as well as the modeling and weather adjustment calculations.

Q. HAVE YOU PREVIOUSLY PROVIDED TESTIMONY BEFORE THE COMMISSION?

A. Yes. I provided weather normalization testimony last year in the Texas New Mexico Power Company ("TNMP") rate case, Docket No. 48401.

Q. WHY DO UTILITIES MAKE WEATHER ADJUSTMENTS AS PART OF RATE CASE FILINGS?

A. Utilities make weather adjustments to normalize energy usage patterns in the test year. By looking at weather data from recent years, we can construct a test year weather pattern that is representative of typical conditions. This insures that rates are not based upon the specific and possibly uncharacteristic weather pattern that occurred in one particular year. This is especially important in a year like 2018 which had weather much colder than normal in some winter months and weather that was warmer than normal in the summer months.

Q. ARE THE TYPES OF WEATHER ADJUSTMENTS YOU DISCUSS IN YOUR TESTIMONY TYPICAL FOR UTILITIES IN RATE CASES?

A. Yes. CenterPoint Houston and other utilities use weather adjustments, including adjustments for monthly sales, customer demand, billing demand, class peaks, and class loads at the time of Company and ERCOT peaks, when designing proposed rates. These adjustments are reasonable and necessary to prepare rates based on energy usage patterns that reflect typical conditions.

Q. ARE THERE IMPORTANT DIFFERENCES BETWEEN THE WEATHER ADJUSTMENTS YOU RECOMMEND IN THIS PROCEEDING AND THOSE MADE IN PAST CENTERPOINT HOUSTON RATE CASES?

A. Yes. There are two notable differences. First, we are able in this proceeding to use advanced meter data that was not yet available when preparing prior cases. In Docket No. 38339, CenterPoint Houston's last rate case, the Company had to use a small statistical sample of customers to estimate hourly usage patterns for each customer class and complex monthly billing data for energy modeling. Today, with advanced meters fully deployed, we can see actual customer demand for every 15-minute interval in every day of every month. These data support exact calculation of daily energy, daily peaks, and daily coincident loads at the time of system peaks, eliminating the statistical uncertainty from sample data. The availability of complete and more granular interval data supports energy and peak adjustment models that are more powerful and accurate than was possible in past rate cases.

A second difference in this proceeding is that we are defining "normal" weather based on a 20-year average instead of a 30-year average, which CenterPoint Houston used in its past few rate cases. Based on industry surveys, the utility industry has shifted to a 20-year average as the most frequently used period for defining normal weather.

Q. DO YOU SPONSOR ANY SCHEDULES IN THE RATE FILING PACKAGE?

A. Yes. I am sponsoring Schedules related to weather adjustment of energy, class peak, class coincident loads, and customer demand. I sponsor or co-sponsor the following Rate Filing Package ("RFP") schedules including the associated workpapers:

Schedule II-H-1.2: Monthly Sales Data – This schedule provides the unadjusted and adjusted test year sales data and provides monthly weather adjustments for each class. My testimony relates to the weather data, modeling, and analysis used to calculate the weather adjustments presented in this schedule and other schedules listed below.

Schedule II-H-1.3: Unadjusted Test Year Load Data – This schedule provides the unadjusted Test Year data at the source (busbar) and at the meter by rate class for each month of the Test Year. Data include the following: Sum of customer maximum demands (non-coincident); Class peak demand (non-coincident); Class demand coincident with the CenterPoint Houston system peak demand; Class demand coincident with the ERCOT peak demand; Energy usage; Monthly class coincidence and load factors.

Schedule II-H-1.4: Adjusted Test Year Load Data – This schedule provides the adjusted Test Year data at the source (busbar) and at the meter by rate class for each month of the Test Year. Data include the following: Sum of customer maximum demands (non-coincident); Class peak demand (non-coincident); Class demand coincident with the CenterPoint Houston system peak demand; Class demand coincident with ERCOT peak demand; Energy usage; Monthly class coincidence and load factors.

Schedule II-H-2.1: Model Information – This schedule provides descriptive information, definitions, and statistics related to statistical models used to estimate weather adjustments to class sales, class peaks, and class demand. The schedule also provides a complete listing of the model spreadsheet files that are provided as exhibits.

Schedule II-H-2.2: Model Data – This schedule provides information about the structure of weather adjustment model spreadsheet exhibit. There is one file per model, and each file includes a complete listing of all data used in the model as well as model coefficients and statistics, model predicted values and residuals, and model statistics. Schedule II-H-2.2 lists the worksheet tabs in each file and provides a description of the contents of each tab.

Schedule II-H-2.3: Model Variables – This schedule provides additional variable definitions for daily weather variables constructed from daily heating degree and daily cooling degree variables, as well as lagged daily weather variables, and weather variables that are interacted with seasonal variables and day type variables. An extension of this schedule (II-H-2.3-1) provides the weights used for each class to combine low-powered, medium-powered, and high-powered heating degree (HD) and cooling degree (CD) variables into the CDSpline and HDSpline variables used in the energy and peak weather adjustment models.

Schedule II-H-4.1: Revenue Impact Data – This schedule provides unadjusted and adjusted billing determinants. These data are on a billing cycle bases and include weather adjustments to revenue month sales (KWh) and customer demand (KVA), customer billing demand (KVA), and customer load at the time of the four ERCOT system peak days.

Schedule II-H-5.1: Weather Station Data – This schedule provides actual and normal monthly Heating Degree Days ("HDD") and Cooling Degree Days ("CDD") for each of the three National Oceanic and Atmospheric Administration ("NOAA") weather stations used in the weather normalization analysis. It also provides weighted monthly CDD and HDD values for CenterPoint Houston.

Schedule II-H-5.2: Adjusted Weather Station Data – This schedule provides actual and normal monthly Heating Degree Day (HDD) and Cooling Degree Day (CDD) values computed for individual billing cycles in each month and then combined across cycles. The cycle calculations assume equal weight for each cycle.

Q. HOW DOES YOUR TESTIMONY RELATE TO THAT OF OTHER WITNESSES IN THIS PROCEEDING?

A. My testimony explains how CenterPoint Houston adjusts energy usage, class peak demands, and billing determinants to reflect normal test-year weather. Company witness Matt Troxle explains how the adjusted weather data are used to design rates.

III. UNADJUSTED TEST YEAR DATA

Q. PLEASE EXPLAIN THE SIGNIFICANCE OF UNADJUSTED TEST-YEAR DATA.

A. Unadjusted test-year data is the starting point for weather adjustment calculations. It is used to estimate models that relate actual energy usage to actual weather conditions in the test year. As described later in my testimony, these models are then used to calculate weather adjustments and adjusted energy usage. The adjusted energy use estimates are then used to compute revenues based on proposed rates.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE UNADJUSTED TEST YEAR LOAD DATA FOR CENTERPOINT HOUSTON AS PROVIDED IN SCHEDULE II-H-1.3.

A. The process starts with 15-minute AMS data for the population of about 2.3 million CenterPoint Houston customers. CenterPoint Houston provided aggregated interval data for each class for 2015 through 2018. In addition to 15-minute consumption, the number of customers included in each 15-minute calculation was provided.

In addition to the AMS data, the Company provided monthly billing data for each class, including the number of customers, billing month energy, actual monthly customer demand, monthly billing demand, and ERCOT monthly 4CP values for the larger IDR classes.

Q. PLEASE DESCRIBE THE STEPS IN PROCESSING THE 15-MINUTE DATA.

A. The 15-minute data for KWh and number of customers were provided for each class. The classes are:

1. RS – Residential
2. SVS – Small secondary voltage
3. SVS_IDR – Small secondary voltage with IDR meter
4. SVL – Large secondary voltage
5. SVL_IDR – Large secondary voltage with IDR meter
6. PVS – Primary voltage
7. PVS_IDR – Primary voltage with IDR meter
8. TVS – Transmission voltage with IDR meter
9. SLS – Street lighting secondary voltage
10. MLS – Other lighting secondary voltage

The KWh and customer data series were inspected graphically in line charts to examine trends, shifts, and spikes in the data. Also, the KWh data were aggregated and compared to CenterPoint Houston system load data.

Q. PLEASE EXPLAIN ANY ADJUSTMENT TO THE TEST YEAR LOAD DATA.

A. No adjustments were made to the test year load data.

Q. PLEASE DESCRIBE THE AMS AND IDR 15-MINUTE DATA.

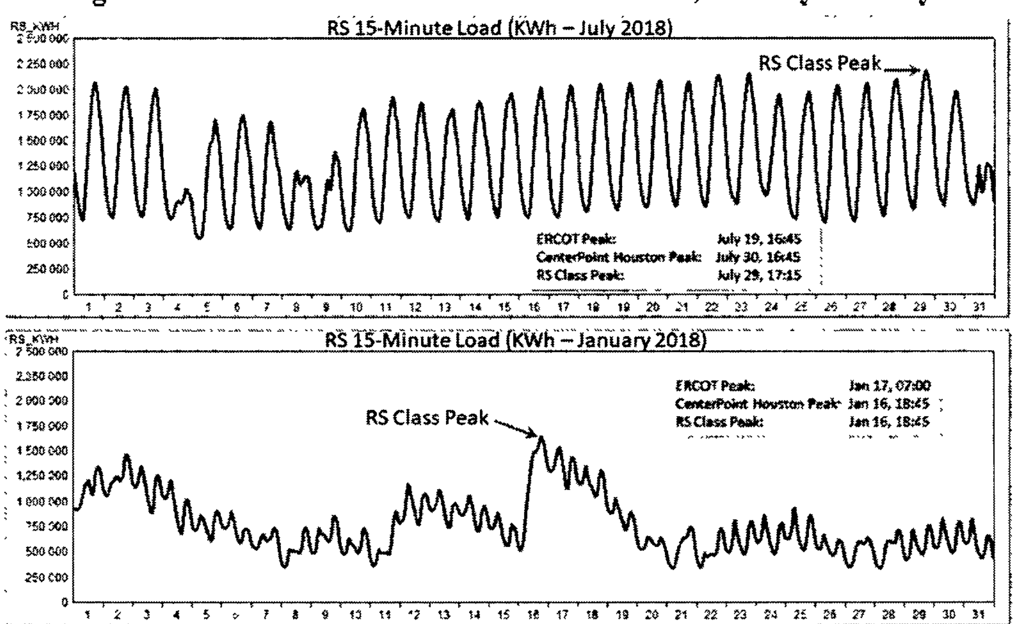
A. 15-minute data were provided for 2015 through 2018. These data were used to calculate daily energy, daily class peaks, and class loads coincident with CenterPoint Houston and ERCOT daily peaks. Definitions of the daily variables follow:

> Daily energy. Daily energy was computed by adding the KWh values for the 96 intervals in each day. These totals were divided by 1000 to convert to MWh.

> Daily class peaks. For each day, class peaks were identified as the maximum of the 15-minute intervals for that day (in KWh) multiplied by 4 to get a KW equivalent value and divided by 1000 to get a MW equivalent value.
>
> Coincident loads. On each day, the intervals for the CenterPoint Houston system peak and ERCOT peak on that day were identified, and the class loads for those intervals were extracted and multiplied by 4 to get a KW equivalent value and divided by 1000 to get a MW value.

An example of the data is provided in the following two panels. The first panel shows data for the residential class in January. The date and time for the ERCOT peak interval, the Company peak interval, and the residential class peak are identified.

Figures 1 and 2. 15-Minute Interval Data for RS, January and July



The second panel shows comparable data for the month of July. In these panels, the times identify the beginning of the 15-minute interval, so 16:45 is for the interval for 16:45 to 17:00. These 15-minute data are used to compute daily energy, daily class peaks, daily loads at the time of CenterPoint Houston and ERCOT peaks, and monthly load factors and diversity factors. The daily data are also used to estimate weather adjustment models for daily energy, daily class peak loads, and loads coincident with CenterPoint Houston and ERCOT daily peaks.

In addition to the aggregated 15-minute interval data, monthly non coincident customer demand data were provided for each class for the months in 2018. To compute this value for a month, the maximum 15-minute interval in the month was located for each customer. These non coincident maximum customer demand values were then summed across all customers in each class.

Q. PLEASE EXPLAIN THE DATA USED TO IDENTIFY THE INTERVALS FOR COINCIDENT PEAK CALCULATIONS.

A. ERCOT 15-minute load data were used to identify the time of the ERCOT peak interval each day. Similarly, settlement data for CenterPoint Houston were used to identify the time of the daily peak interval for the sum of CenterPoint Houston customer loads on each day. Once the peak intervals were identified for each day, the load for those intervals was extracted for each of the classes into a daily series for that class.

Q. HOW WERE LOSS FACTORS APPLIED TO THE AMS INTERVAL DATA TO DETERMINE ENERGY AND PEAK LOADS AT THE SOURCE?

A. AMS data is measured at the customer meter. To inflate these measured values for transmission and distribution losses, we applied distribution loss factors (DLF) and transmission loss factors (TLF) based on 15-minute loss factor data from ERCOT. The Company has two distribution loss factor categories, one for loads at secondary voltage and one for loads at primary voltage. For both categories, ERCOT calculates distribution loss factors for each 15-minute interval based on the ERCOT load in that interval.

The DLF were applied to all classes except Transmission. The TLF were applied to all classes. For all classes except Transmission, the formula for each 15-minute interval is:

Load@Source = Load@Meter * (1+DLF) * (1+TLF)

For the transmission class, the form is the same but the term with DLF is excluded.

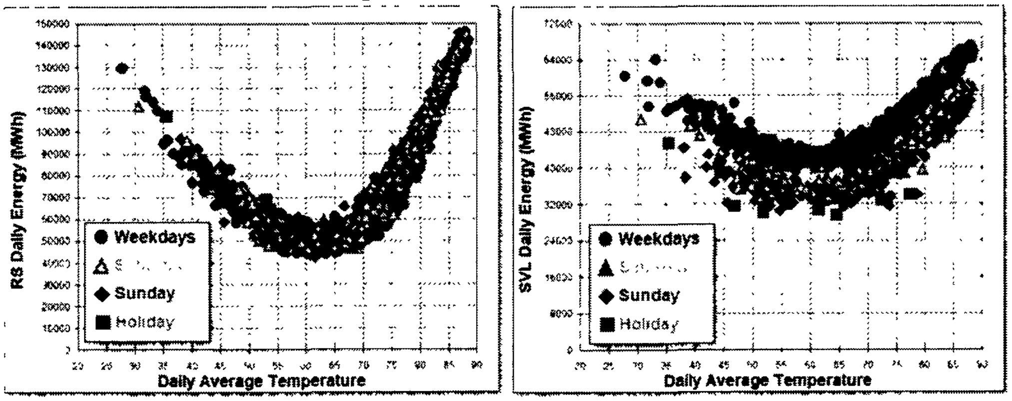
The 15-minute data for Load@Source and the 15-minute data for Load@Meter were then used to compute loss factor multipliers for daily and monthly energy, daily and monthly class peaks, and daily and monthly coincident peaks.

IV. WEATHER ADJUSTMENT MODELS FOR ENERGY

Q. PLEASE EXPLAIN THE MODELING PROCESS USED TO CALCULATE WEATHER ADJUSTMENTS FOR DAILY ENERGY.

A. To adjust test-year energy, we start with models of actual energy usage for each day of the test year. The models are used to calculate daily weather adjustments for each day. The daily adjustments are added across days in the month to get calendar month energy adjustments. The daily adjustments are added across days in monthly billing cycles to get revenue month energy adjustments. The process begins with a review of daily AMS data for each class. As an example, the following figures show scatter plots of daily energy versus daily average temperature for the residential (RS) and large secondary (SVL) classes. These two classes account for more than 90% of the total weather adjustment for the test year.

Figures 3 and 4. Daily Energy vs. Daily Average Temperature for RS and SVL



In the charts, each point is one day. The charts show data for 2015 through 2018, so there are over 1,400 data points in each chart. The Y-axis is daily energy (computed from the 15-minute AMS data) in MWh. The X-axis is daily average temperature, computed from the hourly temperature values for the three weather stations related to the CenterPoint Houston service area. The points are color coded, with weekdays as blue circles, Saturdays as orange triangles, Sundays as red diamonds, and Holidays as green squares.

The charts show us where weather starts to matter on the warm side (about 65 for RS and about 60 for SVL). It also shows that not all degrees are equal and that the early degrees cause a much weaker lift in daily energy than the more extreme degrees. Finally, it shows a very strong heating response on the cold side for RS and SVL classes, starting at about 60 degrees in both cases.

For each class, the modeling process starts by quantifying the nonlinear shape of the weather response using a preliminary regression to determine the relative strength of low-powered, medium-powered, and high-powered degrees for that class. This is accomplished by including multiple Heating Degree and Cooling

Degree variables in the preliminary regression. On the cooling side, the coefficients from this regression are then used to construct a cooling degree spline that combines the successive cooling degree variables. On the heating side, the coefficients from this regression are used to construct a heating degree spline that combines the successive heating degree variables. I believe that the use of these spline variables is an effective and accurate method for modeling the nonlinear relationship between weather and customer load and for calculating weather adjustments for daily energy and daily peak loads.

To illustrate this process, consider the following example for the residential model. The preliminary regression for this class provides the following coefficients on the cooling side.

Figure 5. Example of Preliminary Regression and Spline Weight Calculation

(1) Variable	(2) Estimated Coefficient	(3) Standard Error	(4) T Statistic	(5) Slope (KWh/Degree)	(6) Spline Weight
CD65	0.688	0.054	12.63	0.688	0.263
CD70	0.615	0.108	5.67	1.303	0.235
CD75	0.656	0.109	6.02	1.959	0.251
CD80	0.659	0.087	7.53	2.618	0.252

The estimated coefficients in column (2) are the incremental slopes for each successive cooling degree variable. The models are estimated with daily KWh per customer as the Y variable, so the unit of measurement for these slopes is daily KWh per customer per degree. The first variable (CD65) adds about .69 KWh per degree. Moving above 70 degrees, this jumps up by an additional .61 KWh per degree (for a total slope of 1.30). Moving above 75 degrees, we gain an additional .66 KWh per degree (for a total slope of 1.96). Finally, moving past 80 degrees, we gain an additional .66 KWh per degree (for a total slope of 2.62). In this case, the cumulative slopes indicate that degrees past 80 (CD80) are the most high-powered degrees.

The spline weights are computed from these values by dividing the estimated coefficients by the largest cumulative slope value in column 5. If all coefficients are positive, this normalizes the weights to sum to 1.0. For the residential coefficients shown above, the initial cooling variable for degrees above 65 (CD65) has a spline weight of .263 (computed as .688/2.618), indicating that these degrees have about 26% of the impact of the high-powered degrees. With these weights, the CD spline variable is computed as:

CDSpline = .263 * CD65 + .235 * CD70 + .251 * CD75 + .252 * CD80

The comparable heating degree spline variable is:

HDSpline = .324 * HD60 + .262 * HD55 + .143 * HD50 + .271 * HD45

Once constructed, the daily HDSpline and CDSpline series provide powerful variables that are nonlinear in temperature and that capture the shape of the weather response. These variables are used to estimate models that explain variations in daily energy use per customer based on daily weather variations. As I will show below, the estimated models are then used to compute daily weather adjustments for the test year.

Q. DO THE MODELS FOR DIFFERENT CLASSES USE THE SAME COOLING DEGREE AND HEATING DEGREE VARIABLES?

A. No. Each class is evaluated separately to determine which HD and CD variables should be included. Generally, as customers get larger, the balance point between heating and cooling moves to the left. For small customers, cooling typically begins to show up at 65 and heating begins to show at 60 degrees. For larger customers, weather effects usually start at lower temperatures. For the largest customers, weather effects can be hard to detect. For example, for the largest CenterPoint Houston class (TVS) there was no detectable heating or cooling activity.

The following table shows the HD and CD weights that were estimated for the different classes for purposes of modeling daily energy use. More details are provided in Schedule II-H-2.3 which provides the weights that were used for energy and peak models.

Figure 6. HD and CD Spline Weights for Daily Energy Models

	Heating Degree Weights				Cooling Degree Weights				
Class	HDD60	HDD55	HDD50	HDD45	CDD60	CDD65	CDD70	CDD75	CDD80
RS	0.324	0.262	0.143	0.271		0.263	0.235	0.251	0.252
SVS	0 354	0.264	0.383		0.068	0.213	0 285	0.274	0.160
SVL	0.225	0.121	0.653	-0.207	0.244	0.121	0.273	0.258	0.103
SVL_IDR		1.000			0.382		0.387	0.232	-0.266
PVS	0 366		0.634		0.200	0.146	0.274	0.198	0.183
PVS_IDR	1.000				0.343		0.298	0.359	-0.365

Q. **PLEASE EXPLAIN THE WEATHER ADJUSTMENT MODELS AND HOW THE SPLINE VARIABLES ARE USED IN THESE MODELS.**

A. For energy and class peak demands, the weather adjustment models are daily models. The models include a constant term and a variety of daily calendar variables as well as the HDSpline and CDSpline variables. The calendar variables are:

- Monthly binary variables for January through November (December excluded)
- Day of the week variables for Monday through Sunday (Wednesday excluded)
- Specific holiday variables for holidays from New Year's day through Christmas

- Annual binary variables to account for changes in use per customer
- Class specific binary variables to account for irregular data

In addition to the HDSpline and CDSpline variables, additional weather interaction variables are included in some of the models.

- Two-day weighted lag of HDSpline and CDSpline variables with 85%/15% weights
- Binary variable for weekend and holidays interacted with HDSpline and CDSpline
- Spring day variable interacted with HDSpline and CDSpline
- Fall day variable interacted with HDSpline and CDSpline

The full set of estimated models is included in the working papers filed with this testimony. As an example, the following table provides the estimated coefficients for the residential (RS) daily energy model with a first order Autoregressive term (AR1).

The coefficients that matter for the weather adjustment are the last 10 variables, five for heating and five for cooling. These estimated coefficients all give weather responses in units of KWh per customer per full powered heating degree of per full powered cooling degree. For the residential model, the main Spline variables have very strong statistical significance (T statistics greater than 40), and the lag and interaction variables are also significant (T statistics greater than 2) with the exception of the Spring HDD slope shift which as a T statistic of -1.69.

The LagHD and LagCD variables capture the carryover effect of prior day temperatures onto the current day. For example, for the residential model, the lagged effect for heating is about .34 KWh per degree, which is about 28% of the same-day coefficient on HDSpline (1.24 KWh per degree). For cooling, the lag effect is about .40 KWh per degree, which is about 17% of the same-day coefficient on CDSpline (2.41 KWh per degree).

The weekend interactions (WkEndHD and WkEndCD) allow the weather response to be different for weekend days and holidays than it is for weekdays. For residential heating, the HDSpline slope is estimated to be about .15 KWh per degree smaller on weekend days than it is on weekdays. For residential cooling, the CDSpline slope is estimated to be about .04 KWh per degree bigger on weekend days than it is on weekdays.

For heating, the FallHD variable allows weather response to be different for months leading into winter and the SpringHD variable allows weather response to be different for the months following winter. The estimated coefficients suggest a weaker response for residential heating on both sides of the winter months. The Fall response is estimated to be .23 KWh per degree (or 19%) weaker than the Winter response. The Spring response is estimated to be .12 KWh per degree (or 10%) weaker than the Winter response.

Figure 7. Estimated Coefficients for Residential Model with AR1

Type	Variable	Coefficient	Standard Error	T Statistic	Units of Measure	Definition
	CONST	23.611	0.357	66.208		Constant term
Month	Jan	-0.734	0.417	-1.759	Binary	Binary = 1 in January
Month	Feb	-1.530	0.422	-3.628	Binary	Binary = 1 in February
Month	Mar	-1.112	0.418	-2.660	Binary	Binary = 1 in March
Month	Apr	-0.133	0.421	-0.317	Binary	Binary = 1 in April
Month	May	0.758	0.448	1.692	Binary	Binary = 1 in May
Month	Jun	0.648	0.521	1.244	Binary	Binary = 1 in June
Month	Jul	0.173	0.577	0.301	Binary	Binary = 1 in July
Month	Aug	0.261	0.560	0.465	Binary	Binary = 1 in August
Month	Sep	0.642	0.487	1.319	Binary	Binary = 1 in September
Month	Oct	0.747	0.420	1.778	Binary	Binary = 1 in October
Month	Nov	-0.837	0.388	-2.155	Binary	Binary = 1 in November
Day	Monday	0.456	0.135	3.376	Binary	Binary = 1 on Monday
Day	Tuesday	0.160	0.107	1.497	Binary	Binary = 1 on Tuesday
Day	Thursday	-0.104	0.108	-0.969	Binary	Binary = 1 on Thursday
Day	Friday	-0.224	0.134	-1.673	Binary	Binary = 1 on Friday
Day	Saturday	1.379	0.170	8.114	Binary	Binary = 1 on Saturday
Day	Sunday	2.320	0.168	13.806	Binary	Binary = 1 on Sunday
Holiday	MLK	1.159	0.658	1.761	Binary	Binary = 1 on M L King Day
Holiday	PresDay	1.341	0.651	2.059	Binary	Binary = 1 on Presidents Day
Holiday	GoodFri	0.409	0.602	0.679	Binary	Binary = 1 on Good Friday
Holiday	MemDay	2.091	0.657	3.185	Binary	Binary = 1 on Memorial Day
Holiday	July4th	1.459	0.822	1.775	Binary	Binary = 1 on Independence Day
Holiday	LaborDay	1.987	0.653	3.042	Binary	Binary = 1 on Labor Day
Holiday	Thanks	1.938	0.685	2.830	Binary	Binary = 1 on Thanksgiving Day
Holiday	FriAThanks	-0.009	0.737	-0.012	Binary	Binary = 1 on Friday after Thanksgiving
Holiday	XMasWkB4	2.178	0.972	2.241	Binary	Binary = 1 on week before XMas
Holiday	XMasEve	4.903	1.135	4.318	Binary	Binary = 1 on XMas Eve
Holiday	XMasDay	3.886	0.822	4.730	Binary	Binary = 1 on XMas Day
Holiday	XMasWk	2.471	0.874	2.828	Binary	Binary = 1 during week after XMas
Holiday	NYEve	2.161	1.126	1.919	Binary	Binary = 1 on New Years Eve
Holiday	NYDay	4.222	0.944	4.472	Binary	Binary = 1 on New Years Day
Year	Yr2016	0.359	0.238	1.508	Binary	Binary = 1 for days in 2016
Year	Yr2017	-1.015	0.241	-4.219	Binary	Binary = 1 for days in 2017
Year	Yr2018	-1.853	0.240	-7.717	Binary	Binary = 1 for days in 2018
Heating	HDSpline	1.240	0.028	43.663	DegF	Heating Degree Spline
Heating	LagHD	0.341	0.024	14.394	DegF	Two day lagged HD (85/15 weights)
Heating	WkEndHD	-0.151	0.031	-4.954	DegF	Heating Degree Spline on Weekend Days
Heating	SpringHD	-0.123	0.073	-1.689	DegF	Heating Degree Spline on Spring Days
Heating	FallHD	-0.232	0.062	-3.710	DegF	Heating Degree Spline on Fall Days
Cooling	CDSpline	2.408	0.030	80.346	DegF	Cooling Degree Spline
Cooling	LagCD	0.400	0.028	14.509	DegF	Two day lagged CD (85/15 weights)
Cooling	WkEndCD	0.041	0.017	2.403	DegF	Cooling Degree Spline on Weekend Days
Cooling	SpringCD	-0.270	0.081	-3.333	DegF	Cooling Degree Spline on Spring Days
Cooling	FallCD	-0.342	0.072	-4.756	DegF	Cooling Degree Spline on Fall Days
AR1	AR(1)	0.576	0.022	26.010		

For cooling, the SpringCD variable allows weather response to be different for months leading into Summer and the FallCD variable allows weather response to be different for the months following Summer. The estimated coefficients suggest a slightly reduced response for residential cooling on both sides of the Summer months. The Spring response is estimated to be .27 KWh per degree (or 11%)

weaker than the Summer response. The Fall response is estimated to be .34 KWh per degree (or 14%) weaker than the Summer response.

These coefficients are used to compute daily weather impacts and weather adjustments. The weather impact is the difference between the model predicted value with actual weather and the model predicted value with normal weather. If the weather impact is positive (actual weather was extreme), the weather adjustment will be negative. If the weather impact is negative (actual weather was mild), the weather adjustment will be positive.

As an example of mild weather, February of 2018 was not as cold as normal. As a result, heating energy was less than expected, so a positive weather adjustment for heating was required to bring heating energy back up to normal levels in this month.

As an example of extreme weather, January of 2018 was colder than normal. As a result, heating energy was much higher than expected, so a negative weather adjustment for heating was required to bring heating energy down to normal levels in this month. On the cooling side, the summer months (especially May, June and July) of 2018 were all warmer than normal. As a result, there was extra cooling energy use, and negative adjustments were required to bring cooling energy down to normal levels.

Q. AN AUTOREGRESSIVE ERROR TERM HAS BEEN INCLUDED IN THE WEATHER ADJUSTMENT MODELS. DOES THIS MAKE A DIFFERENCE?

A. Before adding the autoregressive term, it is important to build a strong static model to ensure the right functional form exists. Otherwise, the autoregressive term could disguise a specification problem. In the working papers, both the static model results (without the AR1 term) and the dynamic model results (with the AR1 term) are provided. For example, the following provides the residential model coefficient estimates for the HD and CD variables from both specifications.

Figure 8. RS Daily Energy Model Weather Coefficients

		Static Model (No AR1)			Dynamic Model (with AR1)		
Type	Variable	Coefficient	Std Error	T-Stat	Coefficient	Std Error	T-Stat
Heating	HDSpline	1.300	0.030	42.747	1.240	0.028	43.663
Heating	LagHD	0.343	0.026	13.312	0.341	0.024	14.394
Heating	WkEndHD	-0.206	0.039	-5.247	-0.151	0.031	-4.954
Heating	SpringHD	-0.184	0.063	-2.923	-0.123	0.073	-1.689
Heating	FallHD	-0.212	0.058	-3.668	-0.232	0.062	-3.710
Cooling	CDSpline	2.393	0.033	72.117	2.408	0.030	80.346
Cooling	LagCD	0.370	0.031	11.933	0.400	0.028	14.509
Cooling	WkEndCD	0.029	0.021	1.363	0.041	0.017	2.403
Cooling	SpringCD	-0.110	0.081	-1.372	-0.270	0.081	-3.333
Cooling	FallCD	-0.168	0.065	-2.591	-0.342	0.072	-4.756

The coefficient pattern from the two specifications is consistent, and all coefficient estimates from the two specifications are well within two standard errors of each other in most cases. For example, the CDSpline coefficient is 2.393 KWh per degree in the static model and 2.408 KWh per degree in the model with the AR1 term. Both parameters are strongly statistically significant (t-statistics > 70). The standard error in both models is about .03, so the two slopes are basically the same in a practical sense and in a statistical sense. This coefficient stability is the signature of a strong well specified model.

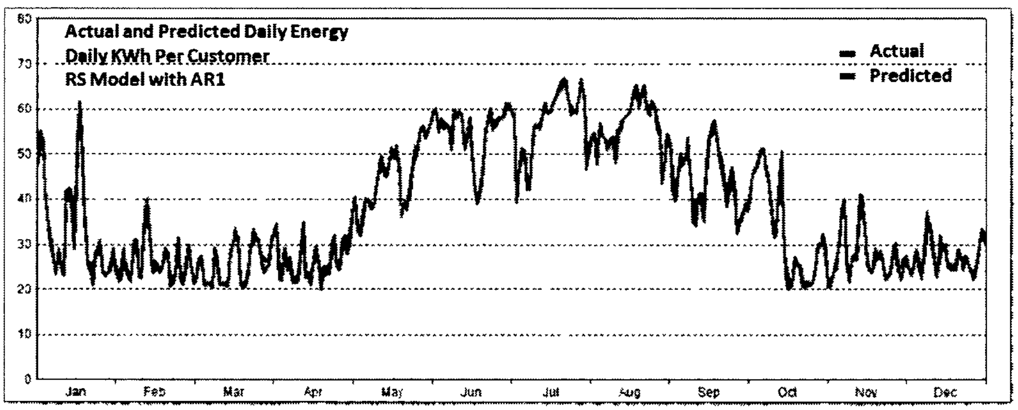
Both sets of models for all classes are included in the working papers filed with this testimony. The weather adjustments presented in the Schedules are from the models with the AR1 terms, but the results would not differ materially if the static models are used.

Q. HOW WELL DO THESE MODELS EXPLAIN THE DAILY VARIATION IN ENERGY?

A. Generally, these models are very strong and explain the daily variations with good accuracy. For example, the following chart shows the actual and predicted daily energy values for the residential model for 2018.

In the chart, the red line is the actual daily energy computed from the 15-minute AMS data and the blue line is the model predicted values. Clearly the model works extremely well throughout the year.

Figure 9. Actual and Predicted Daily Energy for 2018 – Residential Model with AR1



The following provides the model statistics for the static (without AR1) and dynamic (with AR1) residential models.

Figure 10. RS Energy Model Statistics

Residential (RS) Energy Model Statistics	Static Model (No AR1)	Dynamic Model (With AR1)
Adjusted Observations	1449	1449
Deg. of Freedom for Error	1404	1403
R-Squared	0.985	0.990
Adjusted R-Squared	0.985	0.989
AIC	1.053	0.671
BIC	1.217	0.839
Std. Error of Regression	1.67	1.38
Mean Abs. Dev. (MAD)	1.32	1.05
Mean Abs. % Err. (MAPE)	3.87%	3.10%
Durbin-Watson Statistic	0.894	2.067

The quality of the model fit is excellent with mean absolute percent error (MAPE) values of 3.87% for the static model and 3.10% for the dynamic model. The Durbin-Watson statistic provides an indicator of first order autocorrelation. This statistic ranges from 0 to 4 and values that are near 2.0 indicate absence of first order autocorrelation. As values decline toward 0.0, this provides increasing evidence of positive autocorrelation. As values rise toward 4.0, this provides increasing evidence of negative autocorrelation. For the static model, the value of .89 indicates strong positive autocorrelation. With the AR1 correction there is no indication of first order autocorrelation (as indicated by the Durbin-Watson statistic of 2.07).

The following table provides the daily energy model summary statistics for all of the weather sensitive classes. As this shows, the model fit for all classes is strong, with MAPE values ranging between 1.1% and 3.1%.

Figure 11. Model Statistics for Daily Energy Models with AR1

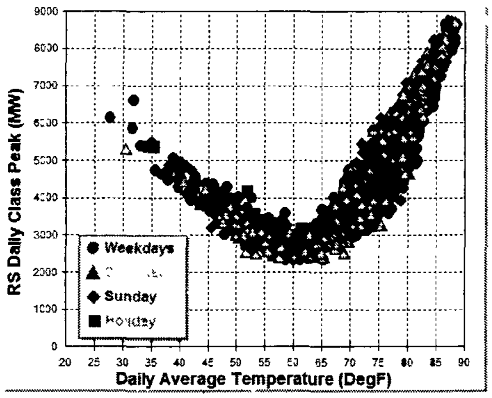
Daily Model Statistic	(RS) Residential	(SVS) Small Secondary	(SVL) Large Secondary	(SVL_IDR) Large Secondary IDR	(PVS) Primary	(PVS_IDR) Primary IDR
Adjusted Observations	1449	1442	1447	1443	1410	1448
Deg. of Freedom for Error	1403	1396	1403	1402	1364	1409
R-Squared	0.99	0.964	0.989	0.985	0.982	0.971
Adjusted R-Squared	0.989	0 962	0.989	0 985	0.981	0 97
AIC	0.671	-2.403	3.919	10 501	7.859	11.806
BIC	0.839	-2 234	4.080	10 651	8.030	11 948
Std Error of Regression	1.38	0 30	6.99	188 02	50.07	361.33
Mean Abs. Dev (MAD)	1.05	0.21	5.04	132 45	36.55	263 51
Mean Abs. % Err. (MAPE)	3.10%	1.10%	1.42%	1.26%	1.84%	1 52%
Durbin-Watson Statistic	2.067	2.141	2.08	1.929	2.206	1 967

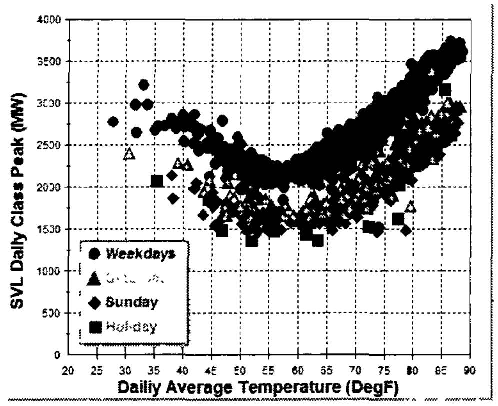
V. WEATHER ADJUSTMENT MODELS FOR CLASS PEAKS AND CP VALUES

Q. PLEASE EXPLAIN THE MODELING PROCESS USED TO CALCULATE WEATHER ADJUSTMENTS FOR CLASS PEAK MODELS.

A. In addition to adjusting energy data to reflect normal weather, for rate design purposes we also need to know about peak loads for each customer class (class peak model), and to know about class loads at the time of overall system peak loads (coincident peak (CP) model). The daily class peak models are similar to the daily energy models, except daily class peak load is the variable that is explained instead of daily energy. As examples, the following figures show scatter plots of daily class peak vs daily average temperature for the residential (RS) and large secondary (SVL) classes.

Figures 12 and 13. Daily Class Peak vs. Daily Average Temperature for RS and SVL





These graphs show weather response patterns for daily class peaks that are similar to the daily energy patterns. However, there are some differences, and as a result, we estimated a different set of HD and CD weights for the class peak and coincident peak models. These weights are shown in the following table.

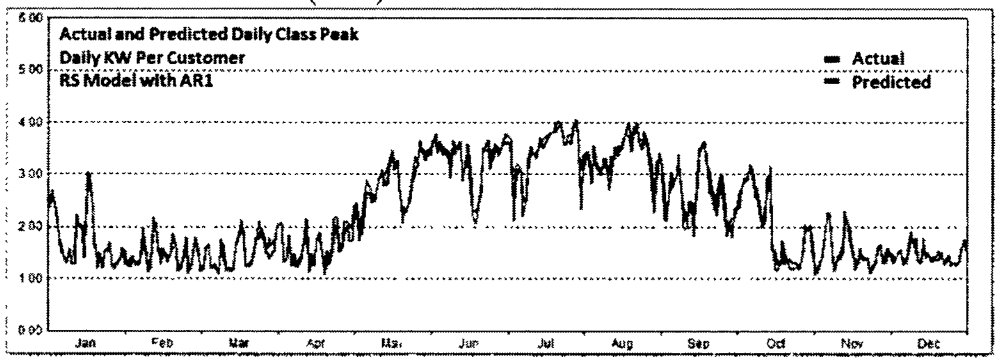
Figure 14. HD and CD Spline Weights for Class Peak Models

	Heating Degree Weights				Cooling Degree Weights				
Class	HDD60	HDD55	HDD50	HDD45	CDD60	CDD65	CDD70	CDD75	CDD80
RS	0.291	0.412	0.297			0.400	0.027	0.265	0.308
SVS	0.211		0.789			0.373		0.279	0.348
SVL	0.435		0.565		0.502		0.139	0.359	-0.111
SVL_IDR		1.000			0.465		0.285	0.250	-0.479
PVS	0.591		0.409		0.372		0.234	0.180	0.214
PVS_IDR	1.000				0.449		0.551		-0.251

The class peak models contain the same set of explanatory variables discussed above for the daily energy models. The working papers filed with this testimony contain spreadsheets that show all of the data used in the models as well as estimated coefficients, model statistics, and actual and predicted values. Spreadsheets are provided for static models and for dynamic models with AR1 adjustments. The models with AR1 adjustments are used to compute the weather adjustments presented in the Schedules.

Like the daily energy models, the class peak models are very strong and explain most of the daily variation in class peaks. For example, the following chart shows the actual and predicted values for the residential daily class peaks in 2018.

Figure 15. Actual and Predicted Daily Class Peak (2018) – Residential Model with AR



The class peak models have errors that are slightly larger than for the energy models. The mean absolute percent errors for these models range from 1.3% (Small Secondary) to 6.2% (Residential). As with the energy models, weather slopes are well defined and strongly significant.

Q. HOW DO THE COINCIDENT PEAK (CP) MODELS DIFFER FROM THE CLASS PEAK MODELS?

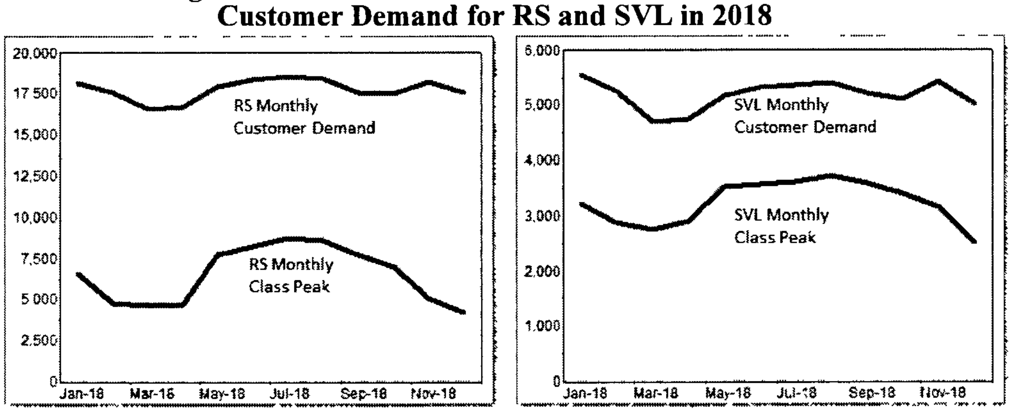
A. Two sets of daily CP models are estimated, one using load at the time of the daily CenterPoint Houston peak and the other using load at the time of the daily ERCOT peak. The CP models use the same set of weather variables and the same model specifications that are used in the daily class peak models. The model estimation results are similar to the daily class peak models in terms of weather parameters and model fit statistics. The full set of model results with and without AR1 terms is included in the working papers filed with this testimony.

VI. WEATHER ADJUSTMENT MODELS FOR CUSTOMER DEMAND

Q. PLEASE EXPLAIN THE MODELS USED TO WEATHER ADJUST CALENDAR MONTH CUSTOMER DEMAND.

A. Customer demand for a calendar month is the sum of the individual customer maximum demands in the month. Customer demand differs from class peak demand since individual customers have maximum demand values on different days in the month and at different times of day. This load diversity implies that customer demand in a month is a bigger number than the class peak demand in the month. The following shows the monthly customer demand and class peak data for 2018 for the residential (RS) and large secondary (SVL) classes.

Figures 16 and 17. Class Peak and Calendar Month Customer Demand for RS and SVL in 2018



For the residential (RS) class, the sum of the monthly customer demand values is almost three times as large as the monthly class peaks. For the large secondary (SVL) class, the sum of the individual customer demands is about 60% larger than the class peaks. Despite the larger scale, there is less variation from month to month in the customer demands as measured by the standard deviations of the monthly values. For example, the standard deviation of the RS demand values is about 40% of the standard deviation of the class peak values.

For the customer demand models, data are only available for 2018, providing 12 monthly observations for each class. As a result of this limited sample size, the weather response models are relatively simple. For the heating side, the models include the largest value of HD55 in each month, representing the coldest day. For the cooling side, the models include the largest value of CD70 for each month, representing the hottest day.

The estimated model coefficients are shown below. Despite the small sample size, the estimated coefficients are statistically significant in almost all cases, as indicated by T-statistics greater than 2.0. The only exception is the coefficient for HD55 in the PVS_IDR equation. This is consistent with the relatively weak response to cold weather for this class. The slopes are in terms of MW per degree, and the largest slopes are for the residential (RS) class and the large secondary (SVL) class.

Figure 18. Estimated Coefficients from Calendar Month Demand Models

	Weighted MaxHD55			Weighted MaxCD70		
Customer Class	Coefficient	Std Error	T-Stat	Coefficient	Std Error	T-Stat
Residential (RS)	68.66	17.13	4.01	115.31	23.50	4.91
Secondary Voltage Small (SVS-Non IDR)	1.21	0.22	5.58	1.87	0.30	6.31
Secondary Voltage Large (SVL-Non IDR)	36.06	4.57	7.89	45.10	6.27	7.19
Secondary Voltage Large (SVL-IDR)	3.77	1.68	2.25	28.43	2.30	12.35
Primary Voltage Service (PVS-Non IDR)	0.68	0.16	4.28	1.09	0.22	4.97
Primary Voltage Service (PVS-IDR)	0.37	0.49	0.74	5.23	0.68	7.72

Because of the small sample size, the customer demand models were estimated without autoregressive error corrections. Inclusion of an AR1 correction would imply losing the first observation (Jan 2018), and this particular observation is critical to determining the response of customer demand to cold weather. Although the models are simple, they explain customer demand very well with mean absolute percent errors below 2% for all classes except the non IDR Primary (PVS) class, which had a MAPE value of 3.26%.

In the working papers, we have provided spreadsheets that contain the data used to estimate these models as well as the estimated coefficients, model statistics, and actual and predicted values.

To calculate weather adjustments for calendar month customer demand, the estimated models are used to simulate predicted customer demands using normal values for the coldest (HD55) and hottest (CD70) days in each month. The difference between the model predicted value with actual inputs and the model simulated value with normal inputs is the weather impact for each calendar month. These impacts are subtracted from the actual demands to give the weather adjusted calendar month demand estimates.

Q. PLEASE EXPLAIN MODELS USED TO WEATHER ADJUST REVENUE MONTH CUSTOMER DEMAND.

A. Revenue month customer demand models are estimated for only two classes, large secondary (SVL) and primary (PVS). These are the only two classes that use actual customer demand directly as a billing determinant.

The actual demand value in a revenue month for a customer corresponds to the largest load that occurs during the days of the billing cycle to which the customer is assigned. Not only are customer demands occurring on different days and at different times, but the set of days included is different for each of the 21 billing cycles. In addition, the number of billing cycles included in a month can vary. For example, in 2018, December and September had only 19 contributing cycles. In contrast, October and August had 23 contributing billing cycles. A difference of 4 cycles would imply an expected 20% variation in energy usage if energy use was flat across all days.

The models are estimated using billing data from the middle of 2015 through 2018. To account for customer growth, the models are estimated based on billing demand per customer. To account for the difference in the number of cycles contributing to each month, the demand per customer values are further normalized to represent 21 full cycles. In equation form, the Y variable in the revenue month demand equation for a class is:

$$Y(m) = (DemandKVA(m)/Customers(m)) * (21/NCycles(m))$$

In this expression DemandKVA is the sum of the customer maximum demand values in KVA and NCycles is the number of billing cycles contributing to revenue in each billing month. Prior to 2018, the cycle adjustment is different for AMS customers and IDR customers. Starting in January 2018, the two billing cycle schedules were converged.

As with the calendar month customer demand, the actual demand values for a revenue month are larger than monthly class peak values, reflecting the diversity in the timing of the individual customer peaks. For example, for the large secondary (SVL) class, the monthly class peaks in 2018 averaged about 3,400 MW, whereas the average of the actual demand values in the revenue months was close to 6,000 MVA.

Billing cycles for a revenue month span days in the current month and prior calendar months. For example in January, typically about half of the cycle energy comes from days in December and half comes from days in January. To reflect this, explanatory variables for a month are calculated as a weighted average of the current and prior month values with 50/50 weights. The first explanatory variable is the monthly class peak normalized by the number of customers in each month. The weighted variable is:

Wgt_NCP_PerCust(m) = .5 * NCP_PerCust(m) + .5 * NCP_PerCust(m-1)

The model is estimated with the actual weighted class peak values and is later simulated with the weather adjusted weighted class peak values.

The customer demands are not necessarily expected to be explained completely by the class peak values, so direct weather variables are also included. To represent the impact of coldest day in each month, the maximum value of the heating degree variable with base temperature 55 is included. The two-month weighted value is computed as follows:

Wgt_MaxHD55 = .5 * MaxHD55(m) + .5 * MaxHD55(m-1)

where MaxHD55(m) is the largest of the daily HD55 values in month m.

Similarly, to represent the impact of the hottest day in each month, the maximum value of the cooling degree variable with base temperature 70 is included. The two-month weighted value is computed as follows:

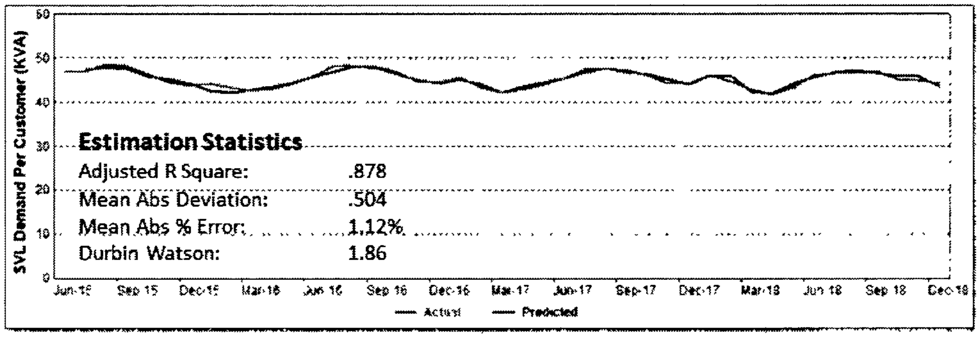
Wgt_MaxCD70 = .5 * MaxCD70(m) + .5 * MaxCD70(m-1)

where MaxCD70(m) is the largest of the daily CD70 values in month m.

The estimated model for the large secondary (SVL) class is shown below. Actual and predicted values from the monthly model are also shown along with key model statistics.

Figures 19 and 20. Revenue Month Billing Demand Model for SVL

Variable	Coefficient	Standard Error	T Statistic	Units	Definition
CONST	29.629	3.147	9.41		
SVL_Wgt_NCP	0.520	0.165	3.15	KWh	Two-month weighted class peak per customer
Wgt_MaxHD55	0.193	0.031	6.34	DegF	Two-month weighted maximum HD55
Wgt_MaxCD70	0.178	0.094	1.88	DegF	Two-month weighted maximum CD70
AR(1)	0.399	0.160	2.50		



In the working papers, spreadsheets are provided for the static and dynamic versions of the model for each class. The spreadsheets contain all data used to estimate these models as well as the estimated coefficients, model statistics, and actual and predicted values. Although the models are very simple, they have strong predictive power, with mean absolute percent errors of 1.9% for SVL and 3.1% for PVS.

To calculate weather adjustments for the revenue month demands, the models are used to simulate predicted demands using weather adjusted values of the current and prior month class peaks and normal values for the current and prior month weather variables. The differences between the model predicted values with actual inputs and the model simulated values with normal inputs are the weather impacts. These impacts are subtracted from the actual values to give the weather adjusted revenue month demand estimates.

Q. PLEASE EXPLAIN THE APPROACH USED TO ESTIMATE WEATHER IMPACTS FOR REVENUE MONTH BILLING DEMAND.

A. For each customer, monthly billing demand is as large or larger than actual demand, reflecting the "ratchet" calculation, which sets billing demand to the larger of the actual demand in a month and 80% of the largest demand in the prior 11 months. For example, in 2018, monthly billing demands for SVL averaged about 6,500 MW, which is about 9% above the average monthly actual demand for the SVL class.

There are four classes that are weather sensitive and that include billing demand as a billing determinant.

- SVL which has actual demand and billing demand as billing determinants
- PVS which has actual demand and billing demand as billing determinants
- SVL_IDR which has billing demand and 4CP as billing determinants
- PVS_IDR which has billing demand and 4CP as billing determinants

For SVL and PVS, we already have models for the actual demand, as discussed above. For these classes, the billing demand model is very simple and specifies billing demand as a function of actual demand. This allows the actual demand weather impacts to be passed through to the billing demand. For the IDR classes, actual demand data were not available. As a result, the billing demand is modeled directly for these classes.

Q. PLEASE EXPLAIN THE MODELS USED TO ESTIMATE WEATHER IMPACTS FOR REVENUE MONTH BILLING DEMAND FOR SVL AND PVS CLASSES.

A. The SVL and PVS billing demand models are estimated with billing demand per customer adjusted for cycles as the variable to be explained and actual demand per customer adjusted for cycles as the explanatory variable. Results for the SVL and PVS models are summarized below. As shown, the coefficients on actual demand are strong and well defined, as evidenced by small standard errors and very high T statistics. The elasticities are .59 for SVL and .89 for PVS, which suggests that ratchets play a relatively weak role for PVS bills. Finally, the models are very precise with average errors of .35% for SVL and 1.84% for PVS.

Figure 21. Slopes and Statistics for SVL and PVS Billing Demand Models

Variable	Actual Demand Slope	Standard Error	T Statistic	Elasticity	Mean Abs % Error	Durbin Watson
Large Secondary (SVL)	0.682	0.027	25.42	0.63	0.35%	2.02
Primary (PVS)	0.994	0.057	17.32	0.89	1.84%	1.26

To calculate weather adjustments for billing demand, the models are used to simulate billing demands using weather adjusted revenue month demand. The differences between the model predicted values with actual demands and the model simulated values with weather adjusted demands are the weather impacts. These impacts are subtracted from the billing demand values to give the weather adjusted revenue month demand estimates.

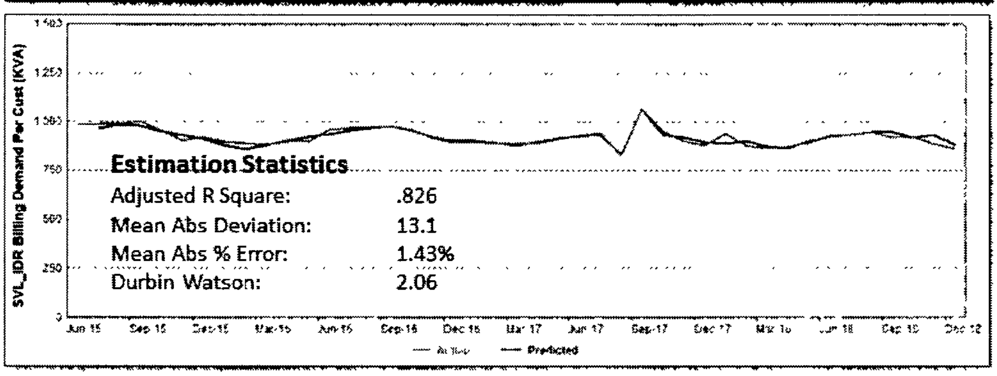
Q. PLEASE EXPLAIN THE MODELS USED TO ESTIMATE WEATHER IMPACTS FOR REVENUE MONTH BILLING DEMAND FOR SVL_IDR AND PVS_IDR CLASSES.

A. The billing demand models for SVL_IDR and PVS_IDR take the same form as the revenue month actual demand models for SVL and PVS. As described above, these models have three inputs that are weighted across the current and prior months. The inputs are (a) the weighted class peak per customer, (b) weighted HD55 for the coldest days, and (c) weighted CD70 for the hottest days. The dependent variable in these models is revenue month billing demand per customer adjusted for the number of cycles.

The model for SVL_IDR is shown below. In addition to the three weighted variables, this model also includes a trinary variable (0, -1, 1) to account for billing data irregularities in August and September of 2017.

Figures 22 and 23. Revenue Month Billing Demand Model for SVL_IDR

Variable	Coefficient	Standard Error	T Statistic	Units	Definition
CONST	455.720	117.238	3.89	KWh	Constant Term
Trinary_AugSept2017	121.072	11.759	10.30	KWh	Trinary = -1 in Aug/17, 1 in Sep/17, 0 otherwise
SVL_Wgt_NCP	0.661	0.199	3.32	KWh	Two-month weighted class peak per customer
Wgt_MaxHD55	2.984	0.870	3.43	DegF	Two-month weighted maximum HD55
Wgt_MaxCD70	2.796	1.496	1.87	DegF	Two-month weighted maximum CD70
AR(1)	0.231	0.167	1.38		



In the working papers, spreadsheets are provided for the static and dynamic versions of the model for each class. The spreadsheets contain all data used to estimate these models as well as the estimated coefficients, model statistics, and actual and predicted values. Although the models are very simple, they have strong predictive power, with mean absolute percent errors of 1.4% for SVL_IDR and 2.2% for PVS_IDR.

To calculate weather adjustments for the revenue month demands, the models are used to simulate predicted demands using weather adjusted values of the current and prior month class peaks and normal values for the current and prior month weather variables. The differences between the model predicted values with actual inputs and the model simulated values with normal inputs are the weather impacts. These impacts are subtracted from the actual billing demand values to give the weather adjusted revenue month billing demand estimates.

VII. NORMAL WEATHER CALCULATIONS

Q. PLEASE DESCRIBE THE DATA AND PROCESS USED TO DEFINE NORMAL WEATHER FOR THE TEST YEAR.

A. To perform daily weather adjustment calculations, it was necessary to define normal daily weather. In order to represent normal weather for both energy and peak calculations a "rank and average" approach was used. This was done with hourly weather data for the 20-year period between 1998 and 2017. In prior decades, the common practice was to use a 30-year period for defining normal weather. Our most recent industry survey in 2017 indicates that a 20-year period is now the prevalent practice. Accordingly, I recommended a 20-year period to define normal weather in performing daily weather adjustment calculations as part of my testimony in Texas New Mexico Power Company's ("TNMP") recent rate case (Docket No. 48401).[1] Darryl Nelson, as witness for Oncor Electric Delivery Company LLC for its recent rate case (Docket No. 46957), also recommended a 20-year period for the weather adjustment calculations.[2] Although both of these cases settled, they reflect that the use of a 20-year period of weather data for the weather adjustment calculations is consistent with current industry practice.

Steps in the approach to define normal weather are as follows:

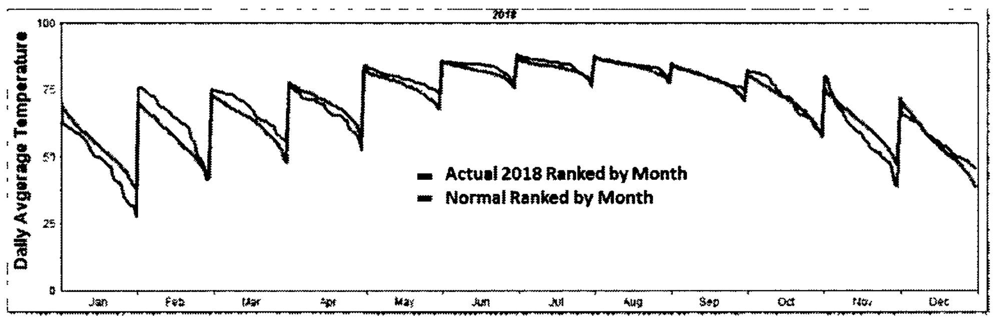
1. Compute daily average temperature for each station and historical day as the average of the hourly values for that day. Stations are Houston International, Houston Hobby, and Sugarland.
2. Compute daily heating degree (HD) and cooling degree (CD) values for each station and each temperature base using the daily average temperature value for each historical day.
3. Combine average temperature, HD, and CD variables across stations using equal weights. The remaining operations are applied to the combined data.
4. Rank the daily data for each historical month and year by sorting the data from hottest to coldest based on the combined daily average temperature.
5. For each month, average the ranked data across the 20-year historical period. This gives an average hottest day, an average second hottest data, and so on through to an average coldest day for each month.
6. Assign the rank-and-average results to days in 2018 based on the weather order that actually occurred in 2018. For example, the coldest day in January 2018 will be assigned the value for the typical coldest day in January. Similarly, the hottest day in July 2018 will be assigned the value for the typical hottest day in July.

The results after the rank and average calculation (step 5 above) are shown in the following chart. This chart shows the result of the process applied to daily average

[1] Docket No. 48401, Direct Testimony of J. Stuart McMenamin, 1618.
[2] Docket No. 46957, Direct Testimony of Darryl E. Nelson, 1531.

temperatures. The green line shows the 20-year rank and average values. The red line shows the actual data for 2018 sorted from highest to lowest within each month.

Figure 24. Comparison of Rank and Average Results and 2018 Daily Average Temperature

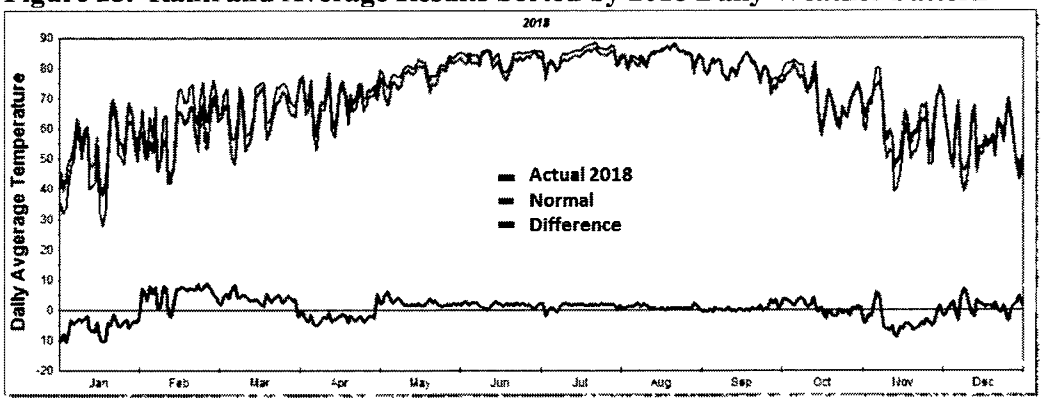


This chart provides a clear picture of how actual and normal weather compare within each month. For example, for January of 2018, the actual values are all below the normal values. The coldest days are well below normal, and this will imply significantly higher than normal heating loads on many days of the month. In contrast, most days in February of 2018 were significantly warmer than normal. This will imply higher than normal cooling loads on the warmest days and lower than normal heating loads on the mild and colder days.

Most of the months in 2018 show warmer than normal temperatures. The exceptions are January (noted above), April, and November, all of which are cooler than normal. For the summer months, June and July show the largest deviations above normal, with August and September showing smaller deviations above normal.

The following chart shows the data for 2018 after Step 6, in which normal values are assigned to days based on the actual 2018 weather pattern. As before, the red line shows actual daily average temperatures, and the green line shows the assigned normal values. The blue line shows the daily deviations. A negative value for the blue line occurs when a day is colder than normal. A positive value for the blue line occurs when a day is warmer than normal. This is the way the modeling process sees the data for observations in 2018. The actual data (red line) are used to estimate models and to compute model predicted values with actual weather. The normal data (green line) are used to simulate models with normal weather.

Figure 25. Rank and Average Results Sorted by 2018 Daily Weather Pattern



As described earlier, the models are based on heating degree (HD) and cooling degree (CD) values for various base temperatures. The following charts show the monthly sum of the HD values, called Heating Degree Days (HDD) and the monthly sum of CD values, called Cooling Degree Days (CDD). Both HDD and CDD values are shown with a base temperature of 65 degrees.

The CDD chart shows that the months of May through September all had more than normal cooling degrees, with the biggest deviations in May, June, and July. The HDD chart shows that the months of January, April, and November had more than normal heating degrees, with the biggest deviation in January.

Figure 26. 2018 Actual and Normal Monthly Cooling Degree Days (CDD Base 65)

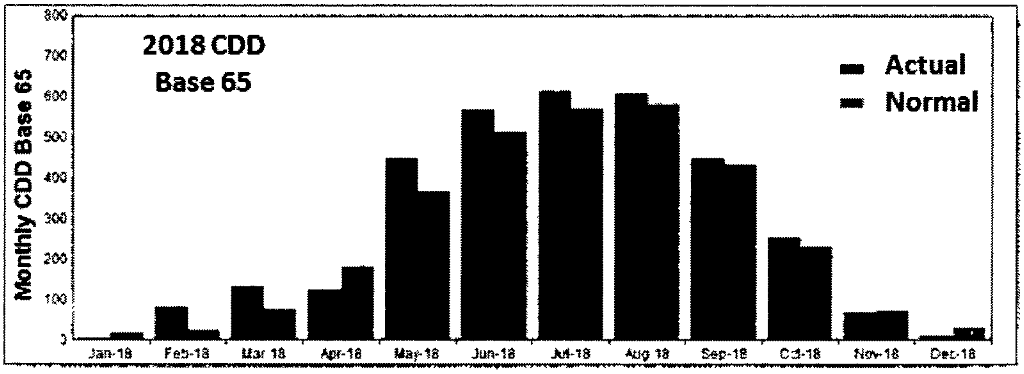
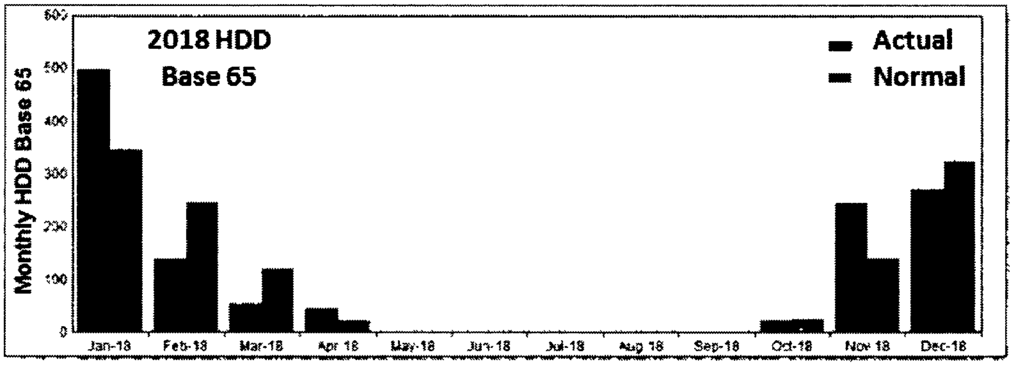


Figure 27. 2018 Actual and Normal Monthly Heating Degree Days (HDD Base 65)



These results show heating and cooling degrees added across all the days in each calendar month. For modeling class peaks, it is also useful to understand how the most extreme weather in each month compares to the normal extreme values. The rank and average calculation gives us a typical hottest day in each month and a typical coldest day in each month. The following charts show the comparison of these typical extremes and the actual hottest and coldest days in each month of 2018.

Understanding these charts helps to explain some of the results that are seen in the demand models. For example, it is expected to see extra demand from heating in January. Extra customer demand from cooling is expected in many months, and even for winter months, like February. In November, both are seen, with increased cooling demands for some customers and increased heating demands for others. And in December, weak customer demands are expected, reflecting weak extremes on both the hot and cold side. This last observation will mainly apply to calendar month demand. Revenue month demands for the December billing month will be mixed, with stronger demands from the cycles with days in November spilling into the December revenue month.

Figure 28. 2018 Actual and Normal Hottest Days (CD65)

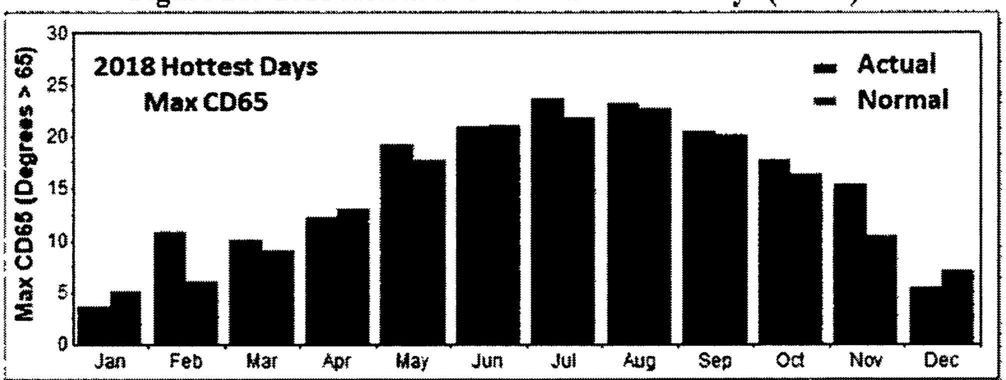
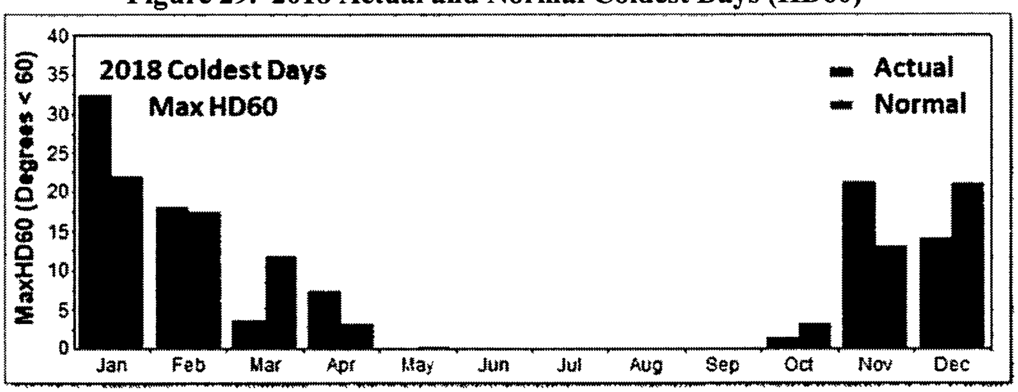


Figure 29. 2018 Actual and Normal Coldest Days (HD60)



More details on weather data are presented in Schedule II-H-5.1 and II-H-5.2.

VIII. SCHEDULES FOR TEST-YEAR SALES DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS REPORTED FOR TEST YEAR MONTHLY SALES IN SCHEDULE II-H-1.2.

A. Weather adjustments to test year energy are computed using daily energy models based on AMS data. Daily energy models are discussed earlier in the testimony and include CD spline and HD spline variables that embody the nonlinear relationship between temperature and daily energy. These variables appear in the models directly and also interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily energy models are estimated with actual daily weather from 2015 to 2018. The estimated models are used to recalculate what daily energy would have been with normal weather on each day. The difference between predicted values with actual weather and predicted values with normal weather is the weather impact. The weather impact is subtracted from actual sales to get adjusted daily sales.

The daily weather impacts from the daily energy models are used to adjust billed sales as reported on Schedule II-H-1.2. Billed sales data represent customer usage over the billing cycles that contribute to each revenue month. For each cycle that contributes to a revenue month, the daily weather impacts are summed across the days in that cycle. These sums are then combined across cycles by assigning an equal weight (1/21) to each cycle. In a revenue month that includes exactly 21 cycles, these weights sum to one. In revenue months with less than 21 cycles, the weights sum to less than one. In revenue months with more than 21 cycles, the weights sum to more than one.

Q. HOW DO THE REVENUE MONTH WEATHER ADJUSTMENTS IN II-H-1.2 COMPARE TO THE CALENDAR MONTH WEATHER ADJUSTMENTS FOR ENERGY IN II-H-1.3?

A. The adjustments follow the same general pattern, but there are some notable differences. For example, calendar month April was a very mild month. This resulted in weak cooling loads and a positive weather adjustment. For the residential class, we estimate that loads in calendar month April would have been about 145 GWh higher with normal weather. In contrast, the billed sales in April reflect weather for days in March and April. Unlike April, March was much warmer than normal, resulting in strong cooling loads and a negative adjustment for most days. The net result when the daily adjustments are combined across the April cycles is a residential adjustment that is close to zero (an upward adjustment of 14 GWh). For some of the business classes, the sign of the weather adjustment in April changes, in that we are adjusting energy upward for calendar month April but downward for billing month April.

The weather adjustments for energy are negative for the year as a whole for both the calendar year and the revenue year. This is true for all classes, and reflects the combination of extra heating from colder than normal weather in January and November and extra cooling from warmer than normal weather in most of the remaining months. For all classes, the billed sales annual adjustments are slightly larger in absolute and percentage terms than the calendar year annual adjustments.

This reflects the fact that December of 2017 had relatively normal weather and did not contribute much to adjustments in the January 2018 billing month. In contrast, December of 2018 had mild weather, leading to positive weather adjustments in the calendar month. On a cycle basis, about half of these positive adjustments get mapped to January of 2019, and therefore do not contribute to the adjustments for 2018 billed sales.

Annual impacts are summarized in the following table for the rate classes that have weather adjustments. For example, for the residential class, the annual adjustment to billed sales is -1,578 GWh which is a 5.16% downward adjustment. On a calendar year basis, the annual adjustment is -1,453 GWh, which is a 4.77% downward adjustment.

Figure 30. Summary of Annual Weather Adjustments for 2018

	Calendar Year		Revenue Year	
Rate Class	**GWh**	**Percent**	**GWh**	**Percent**
Residential (RS)	-1,452.5	-4.77%	-1,578.0	-5.16%
Secondary Voltage Small (SVS-Non IDR)	-10.4	-1.04%	-11.6	-1.25%
Secondary Voltage Large (SVL-Non IDR)	-324.8	-1.80%	-361.2	-1.99%
Secondary Voltage Large (SVL-IDR)	-128.7	-0.90%	-135.9	-0.95%
Primary Voltage Service (PVS-Non IDR)	-6.0	-2.04%	-6.7	-2.29%
Primary Voltage Service (PVS-IDR)	-28.1	-0.72%	-28.8	-0.74%

Summed across all classes, the annual adjustment to billed sales is -2,122 GWh, which is a downward adjustment of 2.33%. On a calendar year basis, the annual adjustment is -1,951 GWh, which is a downward adjustment of 2.15%.

IX. SCHEDULES FOR TEST-YEAR LOAD DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CUSTOMER MAXIMUM DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.

A. Customer maximum demand at the meter is computed from the AMS and IDR 15-minute interval data for each customer. These values are then added across customers to get the actual demand sum for each class in each calendar month.

Because the individual customer demand values come from different days and different hours on those days, there is not a specific loss multiplier that is appropriate to compute demand values at the source. The values at the source on Schedule II-H-1.3 were computed using the distribution and transmission loss multipliers for monthly energy.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS PEAK DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.

A. Class peak demand at the meter is computed directly from the 15-minute interval data summed across customers in each class. Class peak demand at the source is computed from class peak demand at the meter adjusted upward for distribution and transmission loss factors. The loss factors for a month are the 15-minute loss factors that apply for the class peak interval in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS LOAD AT CENTERPOINT HOUSTON PEAK PROVIDED IN SCHEDULE II-H-1.3.

A. CenterPoint Houston peak intervals are determined from 15-minute load data for the CenterPoint Houston system. In each month, the class load in the peak interval is extracted from the 15-minute interval data for that class. This is the class coincident load at the meter.

Class load at the CenterPoint Houston peak interval at the source is computed from the class load at the meter adjusted upward for distribution and transmission loss factors. The loss factors for a month are the 15-minute loss factors that apply at the time of the CenterPoint Houston peak in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS LOAD AT ERCOT PEAK PROVIDED IN SCHEDULE II-H-1.3.

A. ERCOT peak intervals are determined based on 15-minute ERCOT load data published by ERCOT. In each month, the class load in the peak interval is extracted from the 15-minute AMS data for that class. This is the class coincident load at the meter.

Class load at the ERCOT peak interval at the source is computed from the class load at the meter adjusted upward for distribution and transmission loss factors. The loss factors for a month are the 15-minute loss factors that apply at the time of the ERCOT peak in that month.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR ENERGY USAGE AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.

A. Energy usage at the meter is computed from the AMS and IDR 15-minute interval data. For each day, energy is summed across the 96 intervals that contribute to that day. Daily data are summed across days to give the calendar month sum.

Energy usage at the source is computed from the AMS and IDR 15-minute interval data. For each interval, energy use is scaled upward for the distribution and transmission loss factor for that interval. The scaled values are then summed across the 96 intervals that contribute to each day, and the daily values are summed across days. The result is monthly energy by class at the source. The monthly loss multiplier for energy can then be calculated as the ratio of the energy sum with losses to the energy sum without losses.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR CLASS COINCIDENCE FACTORS AND CLASS LOAD FACTORS PROVIDED IN SCHEDULE II-1.3.

A. Class coincidence factors are computed directly from the 15-minute AMS data. For each class, the class peak in a month is identified as the maximum 15-minute value in the month.

Class loads at the time of the ERCOT peak are extracted from the AMS data for the 15-minute interval in which the ERCOT peak occurs.

The value reported as the coincidence factor is the ratio of the class load at the time of the ERCOT peak in each month to the class peak in each month. This value is 100% in months when the class peak occurs exactly at the same interval as the ERCOT peak. Otherwise, it is less than 100%.

Class load factors are also computed directly from the AMS data. For each calendar month, AMS energy is computed as the sum of the class load data for 15-minute intervals that fall in that month. The class peak in a month is identified as the maximum 15-minute value in the month. The load factor is the ratio of the average hourly energy value in a month to the class peak in that month.

X. WEATHER ADJUSTMENTS AND ADJUSTED TEST-YEAR LOAD DATA

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS REPORTED IN SCHEDULE II-H-1.3.1 AND THE WEATHER ADJUSTED ENERGY AND LOAD DATA REPORTED IN SCHEDULE II-H-1.4.

A. Weather adjustments are reported for all classes in Schedule II-H-1.3.1 at the meter and at the source. Adjusted energy and demand values are reported in Schedule II-H-1.4 for all classes. At a high level, the method is the same for all energy and demand concepts. The actual value is calculated from AMS or IDR interval data. The adjustments are computed using statistical models of the daily or monthly data to estimate the impacts of weather deviations from normal. The adjusted values at the meter are computed as the actual value minus the estimated weather impact.

To compute weather adjusted values at the source, the weather adjusted values at the meter are scaled upward for distribution and transmission loss factors. The loss factors applied to the adjusted loads are the same as the loss factors applied to the actual loads.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CUSTOMER MAXIMUM DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.1.

A. The calendar month demand models are discussed earlier in the testimony and include variables for the hottest day (maximum CD70) and the coldest days (maximum HD55) in each month. The models are estimated using monthly data for 2018.

The estimated models are used to simulate demand values with normal weather inputs. The difference between model predicted values with actual extreme weather and simulated values with normal extreme weather are the weather impacts on demand. The weather adjustment values are the inverse of the impact values, and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the actual demand values and the result is further adjusted for customer growth to give adjusted calendar month customer demands as at the meter reported on Schedule II-H-1.4.

For each class, adjusted customer demand at the meter is converted to adjusted customer demand at the source by applying distribution and transmission loss factors computed for monthly energy. These are the same loss factors that are applied to the unadjusted demand data.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS PEAK DEMAND AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.1.

A. Weather adjustments to monthly class peaks are computed using the daily class peak models. Daily class peak models are discussed earlier in the testimony and include CD spline and HD spline variables that embody the nonlinear relationship between temperature and daily class peak. These variables appear in the models directly and also interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily class peak models are estimated with actual daily weather data. The estimated models are used to recalculate what daily class peaks would have been with normal weather on each day. For each month, the difference between the maximum predicted class peak with actual weather and the maximum simulated class peak with normal weather is the class peak weather impact for the month. The weather adjustment values are the inverse of the impact values, and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the actual class peaks, and the result is further adjusted for customer growth, giving the adjusted class peak at the meter reported on Schedule II-H-1.4.

To derive weather adjusted class peak values at the source, distribution and transmission loss factors for the actual class peak interval in each month are applied to the weather adjusted value at the meter.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS LOAD AT THE TIME OF CENTERPOINT HOUSTON PEAK PROVIDED IN SCHEDULE II-H-1.3.1

A. Weather adjustment to class loads at the time of CenterPoint Houston monthly peak are computed using models of daily class coincident loads. Daily loads at the time of CenterPoint Houston peak are computed directly from the 15-minute AMS data based on the time of the Company's peak on each day. Daily coincident load models are discussed earlier in the testimony and include CD spline and HD spline variables. These variables appear in the models directly and also interacting with weekend variables and seasonal variables that allow the weather response to be different on different type of days.

Daily coincident load models are estimated with actual daily weather data. The estimated models are used to recalculate what daily coincident class loads would have been with normal weather on each day. On the Company's peak day in each month, the difference between predicted coincident class load with actual weather and simulated coincident class load with actual weather is the class load weather impact for that month. The weather adjustment values are the inverse of the impact values, and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the actual coincident load values, and the result is further adjusted for customer growth, giving the weather adjusted class coincident load at the meter reported on Schedule II-H-1.4.

To derive adjusted values at the source, distribution and transmission loss factors for the interval of the CenterPoint Houston monthly peak are applied to the adjusted value at the meter.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENTS FOR CLASS LOAD AT THE TIME ERCOT PEAK PROVIDED IN SCHEDULE II-H-1.3.1.

A. Weather adjustment to class loads at the time of ERCOT monthly peak are computed using models of the ERCOT coincident loads for each class. Daily loads at the time of ERCOT peak are computed directly from the 15-minute AMS data based on the time of the ERCOT peak on each day. Daily coincident load models are discussed earlier in the testimony and include CD spline and HD spline variables. These variables appear in the models directly and also interacting with weekend variables and seasonal variables that allow the weather response to be different on different type of days.

Daily coincident load models are estimated with actual daily weather data. The estimated models are used to recalculate what daily coincident class loads would have been with normal weather on each day. On the ERCOT peak day in each month, the difference between predicted class coincident load with actual weather and simulated class coincident load with normal weather is the weather impact for that month. The weather adjustment values are the inverse of the impact values, and are reported on Schedule II-H-1.3.1. The impacts are subtracted from the coincident load value for the month, and the result is further adjusted for customer growth, giving the adjusted class coincident load at the meter reported on Schedule II-H-1.4.

To derive adjusted values at the source, distribution and transmission loss factors for the interval of the ERCOT monthly peak are applied to the adjusted value at the meter.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT RESULTS FOR ENERGY USAGE AT THE METER AND AT THE SOURCE PROVIDED IN SCHEDULE II-H-1.3.1

A. Weather adjustments to calendar month energy are computed using the daily energy models. Daily energy models are discussed earlier in the testimony and include CD spline and HD spline variables that embody the nonlinear relationship between temperature and daily energy. These variables appear in the models directly and also interacting with weekend variables and seasonal variables that allow the weather response to be different on different types of days.

Daily energy models are estimated with actual daily weather data. The estimated models are used to recalculate what daily energy would have been with normal weather on each day. The difference between the predicted daily energy with actual weather and simulated daily energy with normal weather is the weather impact for a day. Daily weather impacts are summed across days in the calendar month. The monthly weather adjustment values are the inverse of the monthly weather impact values, and are reported on Schedule II-H-1.3.1. The monthly weather impacts are subtracted from actual monthly energy values and the result is further adjusted for customer growth, giving the weather adjusted monthly energy at the meter reported on Schedule II-H-1.4.

To derive weather adjusted energy at the source, distribution and transmission loss factors for actual monthly energy in a month are applied to the weather adjusted value at the meter.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE RESULTS FOR ADJUSTED CLASS COINCIDENCE FACTORS AND ADJUSTED CLASS LOAD FACTORS PROVIDED IN SCHEDULE II-H-1.4.

A. Adjusted class coincidence factors are computed from the weather adjusted ERCOT coincident load values and the weather adjusted class peak values, both of which are discussed above.

Adjusted class load factors are computed from the weather adjusted calendar month energy values and the weather adjusted monthly class peak values, both of which are discussed above.

XI. ADJUSTED REVENUE MONTH CUSTOMER DEMAND AND BILLING DEMAND

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR REVENUE MONTH CUSTOMER DEMAND (KVA) PROVIDED IN WORKING PAPER EXHIBIT WP H-4.1.

A. Revenue month customer demand is the sum of maximum customer demands for each billing cycle that contributes to the revenue month. The only classes that have demand as a billing determinant are large secondary (SVL) and primary (PVS). As discussed earlier in the testimony, monthly demand data from the middle of 2015 through 2018 are used to estimate models that use two-month weighted inputs as the explanatory variables. The explanatory variables are monthly class peaks, maximum values of HD55 for extreme cold weather, and maximum values of and HD70 for extreme warm weather.

These models are simulated using weather adjusted class peaks and normal maximum HD55 and HD70 values. For each month, the difference between the predicted value with the actual inputs and the simulated value with the normal inputs is the weather impact. The weather impact for each month is subtracted from the demand value and is further adjusted for customer growth, giving the adjusted revenue month demand value. The unadjusted values, the weather adjustment, and the adjusted monthly values are presented in Schedule WP-H-4.1.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR MONTHLY BILLING DEMAND (KVA) PROVIDED IN WORKING PAPER EXHIBIT WP H-4.1.

A. Revenue month billing demands are larger than customer demand values in a month because of the 80% ratchet calculation. Four weather sensitive classes include billing demand as a billing determinant (SVL, PVS, SVL_IDR, and PVS_IDR). As discussed earlier in the testimony, monthly demand data from the middle of 2015 through 2018 are used to estimate models.

For SVL and PVS, the billing demand model uses actual revenue month demand as the explanatory variable. This allows weather adjustments for monthly demand to be translated into weather adjustments for billing demand.

For SVL_IDR and PVS_IDR, the billing demand model uses the two-month weighted inputs as the explanatory variables, which include monthly class peaks, maximum values of HD55 for extreme cold weather, and maximum values of and HD70 for extreme warm weather.

These models are simulated using weather adjusted values and normal weather values. For each month, the difference between the predicted value with the actual inputs and the simulated value with the normal inputs is the weather impact. The weather impact for each month is subtracted from the billing demand value and is further adjusted for customer growth, giving the adjusted billing demand value. The adjusted and unadjusted monthly values, the weather adjustment, and the adjusted monthly values are presented in working paper exhibit WP H-4.1.

Q. PLEASE DESCRIBE THE PROCESS FOR DETERMINING THE WEATHER ADJUSTMENT FOR ERCOT COINCIDENT DEMAND (4KVA) PROVIDED IN WORKING PAPER EXHIBIT WP H-4.1.

A. ERCOT coincident demand is a billing determinant for two weather sensitive classes, SVL_IDR and PVS_IDR. Demand charges in 2018 are based on coincident load levels in the four summer months of 2017.

Daily models of class loads at the time of the ERCOT peak are discussed above. These models are used to compute daily weather adjustments for 2018, and these adjustments are reported on Schedule II-H-1.3. The models are also used to compute weather adjustments for 2017. These 2017 coincident loads and the associated weather adjustments are shown in the following table. The second to the last row shows the 4CP averages for 2017. The last row shows multiplier for the adjusted 4CP value divided by the actual 4CP value. The adjustments are small, with a .2% downward adjustment for both classes.

Figure 31. Summary of Annual Weather Adjustments

	SVL_IDR 2017			PVS_IDR 2017		
	ERCOT Coincident Loads	Weather Adjustment	Adjusted Coincident Loads	ERCOT Coincident Loads	Weather Adjustment	Adjusted Coincident Loads
June	2,143.3	-2.53	2,145.8	499.06	-0.29	499.35
July	2,165.2	23.83	2,141.3	503.16	5.57	497.60
August	2,351.4	12.83	2,338.6	537.95	2.68	535.27
September	2,180.8	-17.19	2,198.0	509.16	-4.09	513.25
4CP Average	2,210.2	4.23	2,205.9	512.33	0.97	511.37
Multiplier			0.99808			0.99811

These multipliers are applied to the 4CP demand values reported for all months in 2018 as reported on the working paper exhibit WP H-4.1 (Weather Impact).

XII. CONCLUSIONS

Q. **PLEASE SUMMARIZE YOUR TESTIMONY AND RECOMMENDATIONS.**

A. 15-minute AMS and IDR interval data provide the opportunity to understand weather adjustments at a deeper level than was possible with monthly billing data. The 15-minute interval data also provide exact values for daily energy, daily class peaks, and daily coincident load calculations.

Using these data, it is possible to build daily weather adjustment models that account for the nonlinear relationship between load and weather, and to make adjustments that recognize the difference between low, medium, and high-powered degrees. Also, it is possible to identify seasonal differences in the strength of weather response, allowing Spring and Fall responses to differ from Summer and

Winter responses. The result is a set of weather adjustments that are accurate and that are based on powerful statistical relationships. These results provide a strong foundation for revenue requirement calculations based on weather adjusted billing determinants.

Q. ARE THE ADJUSTMENTS DISCUSSED IN YOUR TESTIMONY REASONABLE AND APPROPRIATE?

A. Yes.

Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes, it does.

STATE OF CALIFORNIA §
§
COUNTY OF SAN DIEGO §

AFFIDAVIT OF JOHN STUART MCMENAMIN

BEFORE ME, the undersigned authority, on this day personally appeared John Stuart McMenamin who having been placed under oath by me did depose as follows:

1. "My name is John Stuart McMenamin. I am of sound mind and capable of making this affidavit. The facts stated herein are true and correct based upon my personal knowledge.

2. I have prepared the foregoing Direct Testimony and the information contained in this document is true and correct to the best of my knowledge."

Further affiant sayeth not.

3/9/2019
John Stuart McMenamin

SUBSCRIBED AND SWORN TO BEFORE ME on this 9 day of March, 2019.

KI HOON CHOI
COMMISSION NO. 2132620
NOTARY PUBLIC-CALIFORNIA
SAN DIEGO COUNTY
COMMISSION EXPIRES DEC 1, 2019
CLS1

Notary Public in and for the State of California

My commission expires: Dec. 1, 2019

Dr. J. Stuart McMenamin

Education

- Ph.D., Economics, University of California, San Diego, 1975
- B.A., Mathematics and Economics, Occidental College, 1971

Employment History

- Director of Forecasting Solutions, Itron, Inc., 2002-present
- Senior Vice President, Regional Economic Research, Inc., 1986-2002
- Vice President, Criterion Inc., 1979-1985
- Senior Economist, President's Council on Wage and Price Stability, 1978-1979
- Lecturer in Economics, University of California, San Diego, 1976-1989
- Research Director, Econometric Research Associates, 1975-1978
- Senior Consultant, Institute for Policy Analysis, 1973-1975

Research Experience

Dr. McMenamin is a nationally recognized expert in the field of energy forecasting. Over the last 40 years, he has specialized in the following areas: end-use modeling, energy technology data development, end-use load shape modeling, system load forecasting, price forecasting, retail load forecasting, financial forecasting, load research data analysis, and smart grid data analytics. In addition to his work in the energy area, Dr. McMenamin has completed numerous studies in the areas of telecommunications markets, regional economic modeling, and statistical analysis of employment practices.

Prior to joining Itron, Dr. McMenamin was the principal investigator for the development of the EPRI end-use models (REEPS, COMMEND, and INFORM) which were the primary end-use modeling tools in North America in the 1980s and 1990's. Since joining Itron in 2002, Dr. McMenamin has directed the development of Itron's forecasting software products (MetrixND, MetrixLT, Forecast Manager, and the Itron Load Research System). These products are used by most of the major utilities and ISOs in North America for short-term forecasting and financial forecasting.

In the area of data development, Dr. McMenamin has directed numerous market research studies involving residential, commercial, and industrial customers. These studies have included large on-site survey projects in all sectors, decision-maker studies, vendor surveys, panel of experts studies, and conjoint studies. Results from these studies have been used to construct comprehensive market assessments involving the modeling of customer purchase actions and customer decision processes.

Over the last decade, Dr. McMenamin has spearheaded the development of the Statistically Adjusted End-Use modeling framework, which has been adopted by a growing list of major utilities for long-term forecasting. More recently, Dr. McMenamin has focused on analysis of smart meter data and applications of these data to forecasting, weather normalization, and variance analysis.

Teaching Experience

Undergraduate courses taught at the University of California, San Diego (1976-1989).

- Topics in Economics
- Principles of Microeconomics
- Money and Banking
- International Finance

Selected Reports and Papers

Daily Sales Tracking using AMI Data, presented at AEIC Load Research Committee Meeting, June, 2017

Weather Normalization of VPP Hourly Usage, presented at AEIC/WLR Annual Meeting, August, 2015

Incorporating Energy Efficiency into Western Interconnection Transmission Planning, with Galen Berbose, Alan Sanstad, Charles, Goldman, Andy Sukenik, LBNL-6578E, February, 2014

Weather Normalization by Time of Use, with Rob Zacher, AEIC/WLR Annual Meeting, September 2014.

Modeling an Aggressive Energy-Efficiency Scenario in Long-Range Load Forecasting for Electric Power Transmission Planning, with Alan Sanstad, Galen Barbose, Charles Goldman, and Andrew Sukenik, Applied Energy, Sept 2014.

Forecasting Accuracy Survey and Energy Trends, presented at Energy Forecasting Group annual meeting, April 2014.

Leveraging Meter Data for Distributed Energy Load Forecasting, presented at Analytics for Integration of Distributed Energy Resources panel, IEE Power & Energy Society meeting, July 2013.

Exploratory Data Analysis using Neural Networks, presented at Global Energy Forecasting Competition panel, IEE Power & Energy Society meeting, July 2013.

Smart Grid Analytics, presented at AEIC Load Research Workshop, April, 2013.

Using AMI Data to Improve Forecasting and Financial Analytics, presented at Western Load Research Association, October, 2012.

Links Between Forecasting, Load Research, and Energy Efficiency Analysis, presented at Western Load Research Association, September, 2011.

Demand Response Analytics and other Applications of Smart Grid Data, presented at Western Load Research Association, March, 2010.

Impact of AMI on Forecasting and Load Research, presented at Western Load Research Association, March, 2008. Also Itron white paper available at www.Itron.com.

Defining Normal Weather for Energy and Peak Normalization, Itron white paper, September, 2009. Available at www.Itron.com

Weather Normalization Best Practices Survey, presented at Association of Edison Illuminating Companies, Load Research Workshop, April, 2006.

Using Load Research Data to Estimate Unbilled Revenues, presented at Western Load Research Association, September, 2004

Profiling and Forecasting in Retail Electricity Markets, presented at Advanced Workshop in Regulation and Competition, Center for Research in Regulated Industries, June, 2001.

The Technical Side of ERCOT Profile Models, presented at Western Load Research Association, April, 2001.

Sample Design for Load Profiling, presented at Association of Edison Illuminating Companies workshop, April, 2001.

Neural Networks, What Goes on Inside the Black Box, presented at EPRI Forecasting Workshop, December, 2000.

Evaluating the Decline in Residential Gas Usage, primary author, prepared for Gas Research Institute, May, 2000.

Comparison of Statistical Approaches to Electricity Price Forecasting, with F. Monforte. In *Pricing in Competitive Electricity Markets*, Kluwer Academic Publishers, A. Faruqui and K. Eakin, eds, April, 2000.

Long-term and Short-term Hourly Profile Forecasting Methods. Western Load Research Association Conference, October, 1999.

Load Forecasting for Retail Sales, with F. Monforte. EPRI 12th Forecasting Symposium, April, 1999.

Load Shape Modeling Methods. Presented at EPRI/GRI Workshop on Load Data Analysis, June, 1999.

Short-Term Energy Forecasting with Neural Networks, with F. Monforte, The Energy Journal, Volume 19, Number 4, 1998.

Advanced Methods for Short-term Forecasting. Workshop presented at the IIR Competitive Research and Forecasting Conference, April, 1997.

Benefits of Electrification and End-Use Efficiency. With F. Monforte and P. Sioshansi. *The Electricity Journal*. Volume 10, Number 4, May 1997.

Evaluation of Methods for Estimation of End-Use Load Shapes. Presented at the AEIC Annual Load Research Conference, August, 1997.

Environmental Benefits of Electrification and End-Use Efficiency. Electric Power Research Institute, RP3121-12. January 1996

Integration of DSM Evaluation into End-Use Forecasting. Energy Services Journal, Vol. 1, No.1, 67-79, Lawrence Erlbaum Associates, Inc., 1995 (co-author)

EPRI's Industrial End-Use Forecasting Model - Inform. With F.A. Monforte. Paper presented at EPRI's Ninth Electric Utility Forecasting Symposium, Sept. 1993

Technology Issues in Residential Forecasting and Least-Cost Planning. Proceedings of the Eighth Electric Utility Forecasting Symposium. EPRI TR-100396, 1992

A Statistically Adjusted End-Use Model of Electricity Sales and Peak Demand. With K. Parris. Prepared for Baltimore Gas and Electric Company, November 1988

Commercial End-Use Data Development Handbook. Volume 2: COMMEND Data and Parameter Development Techniques. Electric Power Research Institute. EM-5703, V2. April 1988

An Evaluation of the Subscriber Line Usage System Distribution Analysis Programs. Bell Communications Research. 31230-84-01, February 1984

Measuring Labor Compensation in Controls Programs. With R. Russell. In The Measurement of Labor Cost, ed. Jack E. Triplett, University of Chicago Press, 1983

A Model of Commercial Energy Demand. With I. Domowitz. Energy, 6, No. 12, 1981

The Role of Fiscal Policy in Financially Disaggregated Macroeconomic Models. With D. Cohen. *Journal of Money, Credit and Banking*, August 1978

Specification and Estimation of Dynamic Demand Systems Incorporating Polynomial Price Response Functions. With J. Pinard. *Journal of Econometrics*, July 1978

THERE ARE NO WORKPAPERS

TO

THE DIRECT TESTIMONY

OF

J. STUART MCMENAMIN

APPLICATION OF CENTERPOINT	**§**	**PUBLIC UTILITY COMMISSION**
ENERGY HOUSTON ELECTRIC, LLC	**§**	
FOR AUTHORITY TO CHANGE RATES	**§**	**OF TEXAS**

DIRECT TESTIMONY

OF

MATTHEW A. TROXLE

ON BEHALF OF

CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC

April 2019

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EXECUTIVE SUMMARY OF MATTHEW A. TROXLE

My testimony addresses four areas: (1) the twelve-month period ending December 31, 2018 Test Year ("Test Year") billing determinants used to design the proposed retail delivery service rates; (2) the allocation of costs among the rate classes; (3) the development of CenterPoint Energy Houston Electric, LLC's ("CenterPoint Houston" or the "Company") proposed retail and wholesale delivery service tariff rate schedules, riders and various charges; and (4) other proposed changes to the Company's retail delivery service tariffs. Specifically, my testimony:

- explains the reasonable and necessary adjustments to the Test Year billing determinants that are necessary to make the Test Year billing and usage data more representative of conditions that are expected to exist once new rates go into effect;
- describes the two class cost of service studies used to allocate costs among the rate classes in accordance with the Federal Energy Regulatory Commission System of Accounts, the Public Utility Regulatory Act, the Public Utility Commission of Texas' rules and rate filing package instructions, and the principles of cost causation;
- explains, for both the retail delivery service tariff and the wholesale delivery service tariff, how each rate schedule applies and how each delivery charge is calculated, and also demonstrates that these rate schedules and riders accurately recover the cost of service as described and supported in the rate filing package;
- introduces a new rider, Rider UEDIT – Unprotected Excess Deferred Income Tax, that refunds to customers the balance of unprotected excess deferred income taxes resulting from the Tax Cuts and Jobs Act of 2017 that changed the federal income tax rate in 2018;
- describes the Company's proposed additional charges and discretionary service charges and the methodology used to determine the present cost of providing these services; and
- summarizes other proposed changes to the Company's retail tariff.

The current and proposed base class revenues, inclusive of Rider TCRF, DCRF and UEDIT are as follows:

CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC
SUMMARY OF REVENUES BY RATE CLASS

Rate Class Description	Present Revenues[1]	Proposed Revenues	Rider UEDIT	Change	Change Pct
	(a)	(b)	(c)	(d) = (b)+(c)-(a)	(d)/(a)
Residential	$ 1,130,553,347	$ 1,217,814,820	$ (17,253,347)	$ 70,008,125	6.2%
Secondary <= 10kva	$ 32,594,719	$ 30,607,020	$ (431,501)	$ (2,419,200)	-7.4%
Secondary > 10Kva	$ 654,965,407	$ 739,867,066	$ (10,489,328)	$ 74,412,331	11.4%
Primary	$ 66,701,177	$ 70,089,549	$ (992,514)	$ 2,395,858	3.6%
Transmission	$ 143,211,958	$ 162,433,957	$ (2,313,022)	$ 16,908,977	11.8%
Miscellaneous Lighting	$ 3,843,864	$ 3,126,732	$ (44,200)	$ (761,332)	-19.8%
Street Lighting	$ 63,729,997	$ 58,264,534	$ (834,750)	$ (6,300,214)	-9.9%
Retail Electric Delivery Revenues	$ 2,095,600,469	$ 2,282,203,678	$ (32,358,663)	$ 154,244,545	7.4%
Wholesale Transmission	$ 388,968,021	$ 395,796,573		$ 6,828,552	1.8%
Total Cost of Service	$ 2,484,568,490	$ 2,678,000,251	$ (32,358,663)	$ 161,073,097	6.5%

[1] Test Year revenues have been adjusted to normalize billing units and adjust for DCRF and TCRF

DIRECT TESTIMONY OF MATTHEW A. TROXLE

I. INTRODUCTION

Q. PLEASE STATE YOUR NAME AND CURRENT POSITION.

A. My name is Matthew A. Troxle. I am Director of Regulatory Affairs for CenterPoint Energy Service Company, LLC ("Service Company").

Q. WHAT ARE YOUR PRESENT RESPONSIBILITIES?

A. As Director of Regulatory Affairs, I am responsible for developing and directing regulatory strategy and communicating CenterPoint Energy Houston Electric, LLC's[1] ("CenterPoint Houston" or the "Company") position on complex business and regulatory issues to various parties. In addition, I oversee regulatory filings with the regulatory commissions in the various states in which the Company does business, along with ensuring that regulatory orders and decisions are accurately implemented.

Q. DESCRIBE YOUR EDUCATIONAL BACKGROUND, AS WELL AS YOUR BUSINESS AND PROFESSIONAL EXPERIENCE.

A. I graduated from Louisiana State University in 1995 with a Bachelor of Science degree in Business Administration Pre-Law. In 1997, I received the degree of Master of Science in Economics from Louisiana State University. I began my employment with the Louisiana Public Service Commission in 1997 as an Economist in the Economics and Rate Analysis Division. In 1999, I began employment with the Public Utility Commission of Texas ("Commission") as a

[1] "CenterPoint Energy Houston Electric, LLC" is the legal name for the electric utility company that includes not only the regulated transmission and distribution utility but also the transition bond subsidiaries established to collect transition bond charges and restoration bond charges.

Rate Analyst, in 2000 I was named Senior Rate Analyst, and in 2005, I was named the Director of Retail Market Oversight. In 2007, I was named the Director of Tariff and Rate Analysis. In 2008, I began employment with Service Company as a Manager of Gas Rates in the Regulatory and Government Affairs organization. In 2012, I was named Director of Rates, and in 2015 I assumed the position of Director of Regulatory Affairs.

Q. HAVE YOU PREVIOUSLY PROVIDED TESTIMONY BEFORE THE COMMISSION?

A. Yes. Please see my Exhibit MAT-1 for a list of the Commission proceedings in which I have provided testimony.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING?

A. I am testifying on behalf of CenterPoint Houston, the Applicant in this case.

Q. HAVE YOU PREPARED ANY EXHIBITS?

A. Yes. I sponsor the exhibits shown in my list of exhibits. These exhibits were prepared by me or under my direction and control. The information contained in these exhibits is true and correct to the best of my knowledge and belief.

Q. HOW DOES YOUR TESTIMONY RELATE TO THAT OF OTHER WITNESSES IN THIS PROCEEDING?

A. In general, other Company witnesses sponsor the specific weather adjustments made to billing determinant data, costs and revenue requirements that are incorporated into the cost allocation model, the rate design model, and the proposed tariffs. The direct testimony of Company witness Kenny M. Mercado will present the list of witnesses in this proceeding that will provide further discussion of the topics.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY IN THIS PROCEEDING?

A. The purpose of my testimony is to: (1) sponsor the proposed twelve-month period ending December 31, 2018 ("Test Year") billing determinant adjustments made to energy sales, demands, and year-end customer count; (2) present CenterPoint Houston's Class Cost of Service Study ("CCOSS") in support of the Company's proposed delivery system charges in its Tariff for Retail Delivery Service ("Retail Tariff") and the Company's proposed wholesale transmission rates in its Tariff for Wholesale Transmission Service ("WTS Tariff"); (3) support the calculation of the proposed delivery system and discretionary service charges in its Retail Tariff, and the proposed wholesale transmission rates in its WTS Tariff; (4) explain the policy reasons for any proposed rate design changes for delivery system charges in the Retail Tariff; and (5) support the proposed non-rate changes to various provisions in Chapters 2 and 6 of the Retail Tariff. In my testimony, the terms "delivery system charges" and "discretionary charges" have the respective meanings given for those terms in Section 1 of the Retail Tariff.

Q. DO YOU SPONSOR ANY SCHEDULES IN THE RATE FILING PACKAGE?

A. Yes. I sponsor or co-sponsor the following Rate Filing Package ("RFP") schedules that relate to and support the Company's Test Year Customer Billing Determinant Data, CCOSS, Class Cost Allocation process, and Rate Design process:

- Schedule II-H-1: Summary of Test Year Adjustments – This schedule provides the following summary of Test Year data by rate class: year-end number of customers, total adjusted kWh sales.

- Schedule II-H-1.1: Test Year Sales Data – This schedule provides the following Test Year data by rate class: average number of customers, year-end number of customers; Test Year kWh (unadjusted sales), increase or decrease in kWh sales due to adjustments for abnormal weather, increase or decrease in kWh sales due to adjustments for changes in customer composition and/or for changes in the number of customers; increase or decrease in kWh sales due to adjustments other than for the effects of weather and customer (e.g. reclassification of customers), reflecting each adjustment separately; and total adjusted kWh sales for the Test Year.

- Schedule II-H-1.2: Monthly Sales Data – This schedule provides the data presented in Schedule II-H-1.1 by month of the Test Year.

- Schedule II-H-1.5: Adjustments to Operating Statistics – The schedule provides a narrative explanation for all adjustments made to Test Year operating statistics provided above in Schedule II-H-1.

- Schedule II-H-3.1: Customer Information – This schedule provides the monthly Test Year number of customers by rate class.

- Schedule II-H-3.2: Customer Adjustments – This schedule presents topics and descriptions of the customer adjustments performed by rate class.

- Schedule II-H-3.3: Customer Adjustment Data – The purpose of this schedule is to provide adjustment data not already presented in Schedule II-H-3.1 above. This schedule is not applicable, CenterPoint Houston has provided all the customer adjustment data above in Schedule II-H-3.1.

- Schedule II-H-4.1: Revenue Impact Data – Provides the Test Year data on revenue impacts of kWh sales and kW/kVA demand adjustments by rate class. The data columns show: revenue associated with any rate annualization adjustments, showing components separately; revenues associated with kWh customer adjustments, showing components separately; revenues associated with kW customer adjustments, showing components separately; revenues associated with kWh weather adjustments, showing components separately; revenues associated with kW weather adjustments, showing components separately; revenues associated with other kWh adjustments, showing the revenue associated with each adjustment individually, listing components separately; revenues associated with other kW adjustments, showing the revenue associated with each adjustment individually, listing components separately.

- Schedule II-H-4.2: Revenue Calculation Methodologies – This schedule provides a description of the methodologies used to calculate the adjustments to revenues.
- Schedule II-I-1: Class Revenue Requirement Analysis – Provides a class revenue requirement analysis for the Test Year and displays the functional revenue requirement allocated to each rate class.
- Schedule II-I-2 Class Allocation Factors – Provides the allocation factors used in each customer class.
- Schedule II-I-3 Functionalized Cost-of-Service Analysis (Non-ERCOT Members) – Because CenterPoint Houston is a member of ERCOT, this schedule is not applicable.
- Schedule IV-J-1 Revenue Summary – This schedule provides a summary of the Test Year revenue requirement. The rows of the table display the Test Year revenue requirement by base rate function and approved riders. The columns display the Test Year revenue requirement by rate class.
- Schedule IV-J-2 Proposed Charges for Discretionary Services and Other Services – Provides the proposed charges for each discretionary and other service charge in the Company's tariffs.
- Schedule IV-J-3 Rate Class Definition – Catalog of rate classes and definitions.
- Schedule IV-J-5 Billing Determinants – This schedule imparts the following billing summary for each rate class for each month of the Test Year: Billing Demand, Billing kWh, and Number of Customer Bills. Billing Demand details unadjusted, adjustments, and fully-adjusted total. Billing kWh details unadjusted, adjustments (weather and customer changes, and Energy Efficiency Program) and the total fully-adjusted kWh totals. Number of Customer Bills unadjusted, customer growth adjustment, fully-adjusted total.
- Schedule IV-J-6 Justification for Consumption Level-Based Rates – This schedule is not applicable.
- Schedule IV-J-7 Proof of Revenue Statement – This schedule provides a proof of revenue statement, presents the class cost of service, the billing units, proposed rates, and the resulting base revenue for the existing and proposed rate classes, and any other Commission-approved non-bypassable charges under both current and proposed rates.
- Schedule IV-J-8 Rate Design Analysis Data – Provides estimated billing determinants, without ratchet provisions, for peak and off-peak periods as