

OFFICIAL  
EXHIBIT

FILED  
March 2, 2020  
INDIANA UTILITY  
REGULATORY COMMISSION

STATE OF INDIANA

INDIANA UTILITY REGULATORY COMMISSION

IN THE MATTER OF THE VERIFIED )  
PETITION OF INDIANA MICHIGAN POWER )  
COMPANY FOR APPROVAL OF DEMAND )  
SIDE MANAGEMENT (DSM) PLAN, )  
INCLUDING ENERGY EFFICIENCY (EE) )  
PROGRAMS, AND ASSOCIATED )  
ACCOUNTING AND RATEMAKING )  
TREATMENT, INCLUDING TIMELY )  
RECOVERY THROUGH I&M'S DSM/EE )  
PROGRAM COST RIDER OF ASSOCIATED )  
COSTS, INCLUDING PROGRAM )  
OPERATING COSTS, NET LOST REVENUE, )  
AND FINANCIAL INCENTIVES. )

IURC  
PETITIONER'S

EXHIBIT NO. 5  
DATE 10-15-20 REPORTER LR

CAUSE NO. 45285

SUBMISSION OF REBUTTAL TESTIMONY OF  
CHAD M. BURNETT

Applicant, Indiana Michigan Power Company (I&M), by counsel, respectfully  
submits the rebuttal testimony and attachments of Chad M. Burnett in this Cause.



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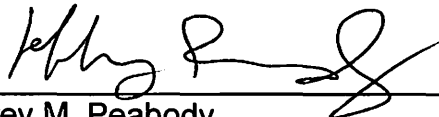
## CERTIFICATE OF SERVICE

The undersigned certifies that the foregoing was served upon the following via electronic email, hand delivery or First Class, or United States Mail, postage prepaid this 2nd day of March, 2020 to:

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**STATE OF INDIANA**  
**INDIANA UTILITY REGULATORY COMMISSION**

**INDIANA MICHIGAN POWER COMPANY**

**PRE-FILED REBUTTAL TESTIMONY**

**OF**

**CHAD M BURNETT**

**PRE-FILED REBUTTAL TESTIMONY OF CHAD M BURNETT  
ON BEHALF OF  
INDIANA MICHIGAN POWER COMPANY**

**I. Introduction**

**Q. Please state your name and business address.**

A. My name is Chad M. Burnett, and my business address is 212 East 6<sup>th</sup> Street, Tulsa, Oklahoma 74119.

**Q. By whom are you employed and in what capacity?**

A. I am employed by American Electric Power Service Corporation (AEPSC) as the Director of Economic Forecasting. AEPSC supplies engineering, financing, accounting, planning, advisory, and other services to the subsidiaries of the American Electric Power (AEP) system, one of which is Indiana Michigan Power Company (I&M or the Company).

**Q. Please briefly describe your educational and business experience.**

A. I received a Bachelor of Science degree in Business Administration from the University of Tulsa in 1998 with emphasis in Economics and Finance. In 2002, I received a Master of Business Administration degree from the University of Tulsa. In 2005, I completed the Executive Strategic Leadership program at Ohio State University.

I have worked in the utility industry as an economist since 1997 when I was employed by Central and South West Service Corporation, which later merged with AEP in June 2000. I became the Manager of Economic Forecasting in June 2007. In October 2013, I was promoted to Director of Economic Forecasting. In my current role, I am responsible for preparing customer, sales,

peak demand, and revenue forecasts for each of the AEP operating companies in the eleven jurisdictions and three regional transmission organizations (RTOs) that cover the AEP service territory. In addition, I am responsible for the weather normalization calculations and sales and revenue variance reports for each of the AEP operating companies including I&M.

**Q. Have you previously testified in any regulatory proceedings?**

A. Yes, I have testified before the Indiana Utility Regulatory Commission (IURC or Commission) in several cases, including Cause Nos. 44967 and 45235. In addition I have also provided testimony before regulatory commissions in the states of Arkansas<sup>1</sup>, Michigan<sup>2</sup>, Oklahoma<sup>3</sup>, Tennessee<sup>4</sup>, Texas<sup>5</sup>, and Virginia<sup>6</sup>.

**Q. What is the purpose of your rebuttal testimony in this proceeding?**

A. The purpose of my rebuttal testimony is to respond to the portions of testimony offered by Citizens Action Coalition of Indiana, Inc. (CAC) witness Anna Sommer concerning the load forecast that was used as an input in I&M's Integrated Resource Plan (IRP).

Specifically, I will address CAC's claim that I&M's modeling of the demand-side management (DSM) assumptions was "distorted" (at 3) and the resulting load forecast that went into the IRP modeling was too high. I respond to and refute Ms. Sommer's arguments regarding I&M's use of degradation and

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<sup>1</sup> Docket No. 19-008-U in 2019.

<sup>2</sup> Case No. U-20359 in 2019 and Case No. U-20591 in 2020.

<sup>3</sup> Cause No. 20080014 in 2008 and Cause No. 201800097 in 2019.

<sup>4</sup> Docket No. 16-00001 in 2016.

<sup>5</sup> Docket No. 36966 (2009), Docket No. 37364 (2009), Docket No. 40443 (2012), Docket No. 44701 (2015), Docket No. 46449 (2016), and Docket No. 49494 (2019).

<sup>6</sup> Case No. PUR-2017-00174 (2018) and Case No. PUR-2018-00051 (2018).

1 explain why I&M's degradation approach is reasonable and necessary to arrive  
2 at a reasonable load forecast for DSM planning purposes.

3 **Q. Are you sponsoring any attachments with your rebuttal testimony?**

4 A. Yes I am sponsoring the following attachments:

- 5 • Attachment CMB-1R – Presentation from I&M's 2<sup>nd</sup> IRP Stakeholder  
6 Meeting held on April 11, 2018.
- 7 • Attachment CMB-2R – Itron White Paper on Incorporating DSM into the  
8 Load Forecast

9 **Q. Were these attachments prepared or assembled by you or under your**  
10 **direction and supervision?**

11 A. Yes.

12 **II. I&M's Load Forecast Methodology is Reasonable**

13 **Q. CAC witness Sommer (at 3) claims "that I&M's 2018-2019 IRP is**  
14 **irredeemably flawed" especially with regards to the way the DSM**  
15 **assumptions were modeled in the load forecast. Do you agree with CAC's**  
16 **position regarding the IRP and the load forecast methodology?**

17 A. No I do not. Much of the CAC's criticism of the IRP modeling focuses on the  
18 degradation approach used in I&M's load forecast. I specifically rebut Ms.  
19 Sommer's criticisms of the degradation approach below. I would first note,  
20 however, that the Company's load forecast methodology is proven to produce  
21 accurate and reliable projections that are useful for planning and setting rates.  
22 The Company used the same load forecast methodology in the 2018-19 IRP as it

has in previous IRPs, base rate cases, fuel cost adjustment filings, financial forecasts, *etc.* In other words, this proven methodology has been accepted by the Commission in various regulatory proceedings. Moreover, this methodology has produced accurate results, as discussed further below.

**Q. Has staff from any state regulatory commission reviewed the load forecast and load forecast methodology from I&M's 2018-19 IRP?**

A. Yes. In Michigan, Staff witness Roger A. Doherty from the Michigan Public Service Commission testified in Case No. U-20591 (I&M's 2018-19 IRP filing) that the Company's "energy sales and peak demand forecasts [were] consistent with other load growth projections in the region" (at 5), that "the Company's high and low growth forecasts [were] reasonable" (at 6), that "the Company's forecasting methodology with respect to weather aligns with industry norms" (at 7), and that "the load forecasts used by the Company in the IRP are reasonable" (at 7).

In Indiana, the IURC staff are currently reviewing I&M's 2018-19 IRP and have yet to publish the final Director's Report. However, the Company has used the same load forecast methodology and approach to modeling DSM programs since 2010 and the Director's Report on I&M's last IRP offered a detailed assessment of I&M's load forecast methodology and DSM analysis.<sup>7</sup> That Director's Report states, "the Director believes that I&M's load forecast

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<sup>7</sup> IURC Electricity Director's Final Report 2015-2016 Integrated Resource Plans submitted by Duke Energy, Indiana Michigan, Indiana Municipal Power Agency, and Wabash Valley Power Association, August 30, 2016, available at: <https://www.in.gov/iurc/files/Consolidated%20IRP%20Report%20for%20DEI%20IM%20IMPA%20and%20WVPA%20-%20Final%208-30-16.pdf>

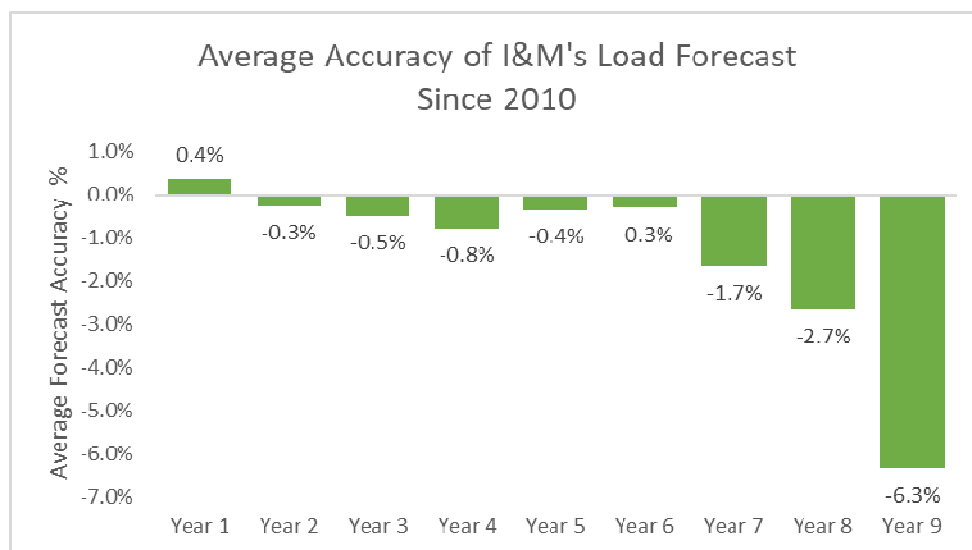
methodologies, analytical tools, databases, and processes are reasonable.”<sup>8</sup>

Finally, it is noteworthy that I&M uses the same load forecast methodology in the IRP as is used in I&M’s base rate cases, fuel adjustment clause filings, and other rider filings before the Commission. The Company is confident in doing so because the load forecast methodology is proven to produce accurate and reliable projections that are useful for planning and setting rates.

**Q. In response to witness Sommer’s claim that the forecast is “irredeemably flawed” (at 3 and 4), please describe the accuracy of I&M’s prior load forecasts that used the same methodology.**

A. Figure CMB-1R below shows the average accuracy of every I&M load forecast over the past decade. On average, I&M’s load forecasts have been within 0.8% of the actual results through the first 6 years. Even at year 8, I&M’s load forecast has been within - 2.7% of the weather normalized actuals.

**Figure CMB-1R**



<sup>8</sup> Page 12.



1 This data confirms that the Company's load forecast methodology is proven to  
2 produce accurate and reliable projections that are useful for planning and setting  
3 rates. Furthermore, this contradicts Ms. Sommer's claim that the forecast  
4 methodology used in the IRP is 'irredeemably flawed'.

5 **III. I&M's Degradation Approach Properly Models DSM Savings in the IRP**

6 **Q. On page 5 of her testimony, CAC witness Sommer criticizes the Company's**  
7 **degradation approach, stating "I&M's adjustment to energy efficiency neither**  
8 **appropriately accounts for it in the load forecast nor is actually reflective of**  
9 **how energy efficiency programs accrue savings." Please respond.**

10 **A.** There are a number of problems with Ms. Sommer's assessment of the Company's  
11 modeling of DSM savings, both in her testimony and in the IRP comments she  
12 includes as her Attachment AS-2. She has confused and misrepresented a  
13 number of items with respect to how the Company is accounting for energy  
14 efficiency in the load forecast. Furthermore, her view of how utilities in the industry  
15 are modeling DSM savings with their load forecast models has led to a conclusion  
16 that is not accurate with respect to I&M. Finally, the logic behind her argument is  
17 flawed. I discuss these points in greater detail below.

18 **Q. On pages 4-5 of her testimony, CAC witness Sommer states that I&M's use of**  
19 **degradation "does not mean what is typically meant by this term, i.e. the**  
20 **change in measure performance over time." Please explain what I&M means**  
21 **by the term "degradation" in the context of IRP modeling.**

22 **A.** Stated simply, "degradation" refers to the need to adjust I&M's base load forecast to

1 avoid double counting energy efficiency savings already reflected in the load  
2 forecast. While it may not always be referred to as “degradation”, this concept is  
3 well-recognized in the realm of IRP modeling.<sup>9</sup> As described in section 2 of the  
4 IRP, the Company uses Itron’s Statistically Adjusted End-Use (SAE) models for  
5 long-term planning. It is important to recognize that this baseline SAE load forecast  
6 is not a “no DSM forecast”. Rather, as explained on page 24 of I&M’s IRP, the  
7 “initial base load forecast accounts for the evolution of market and industry  
8 efficiency standards.” I&M’s degradation approach avoids the double counting of  
9 energy efficiency that would otherwise occur absent such an adjustment.

10 **Q. CAC witness Sommer (at 4-5) defines degradation as “the change in measure**  
11 **performance over time”. When I&M runs the gross DSM savings through the**  
12 **degradation matrix, is the Company accounting for more than just the**  
13 **change in measure performance over time?**

14 **A.** Yes. The Company’s use of the term ‘degradation’ encompasses more than Ms.  
15 Sommer’s narrow interpretation. In addition to the fact that appliances lose certain  
16 operational efficiencies over time, the degradation matrix is also accounting for  
17 market adoption rates and other DSM measurement issues (stipulated vs verified  
18 savings, net-to-gross savings, free ridership, spillover, *etc.*)

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<sup>9</sup> Attachment CMB-2R is a white paper published by Itron that describes how utilities have modeled DSM savings within the SAE framework. The Company’s approach is closer to Method 2 described in the report.

1 **Q. On page 6 of her testimony, CAC witness Sommer asserts the “application of**  
2 **degradation to energy efficiency bundles is wholly inappropriate”. Can you**  
3 **explain why the Company’s methodology is appropriate?**

4 **A.** Yes I can. As noted above, the primary reason we degrade the DSM savings in the  
5 load forecast methodology is to prevent double counting energy efficiency savings  
6 already embedded in the load forecast. As explained in I&M’s IRP, “[t]he SAE  
7 models were designed to account for changes in the saturations and efficiencies of  
8 the various end-use appliances.”<sup>10</sup> If we were to subtract from the load forecast the  
9 gross savings from the DSM programs, we would be double counting energy  
10 efficiency impact in the load forecast. The result would be that our long term load  
11 projections and capacity requirements would be substantially understated.

12 **Q. CAC witness Sommer also claims (p. 6) that degradation “serves to make**  
13 **energy efficiency potential look much smaller than it actually is in practice.”**  
14 **If the Company did not employ its degradation matrix to the gross DSM**  
15 **savings (consistent with the CAC’s recommendation), what would be the**  
16 **impact on I&M’s load forecast that already has levels of energy efficiency**  
17 **included?**

18 **A.** The load forecast would be understated. In fact, in I&M’s recent Michigan base rate  
19 case (Case No. U-20359), MPSC Staff witness Karen M. Gould identified that exact  
20 argument. She pointed out that, “[u]tilizing savings which are stipulated could skew  
21 the forecasted sales projections<sup>11</sup>.” In response to Staff’s concern in the base rate

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<sup>10</sup> From I&M’s filed IRP, section 2.6.1, pg. 22.

<sup>11</sup> Case No. U-20359 Direct Testimony of Staff witness Karen M. Gould, pg. 6.

case, I&M stated:

That is one of many reasons why the Company utilizes a degradation approach to the savings from the [DSM] reports to prevent overstating the impact of energy efficiency in the load forecast.”<sup>12</sup>

More fundamentally, Ms. Sommer’s statement assumes that future DSM savings must always be at or above whatever savings amounts I&M was able to achieve historically. That is simply not the case. Generally speaking, utilities started their DSM programs addressing the low-hanging fruit of lighting. As the saturation of efficient lighting has grown, and without the support of additional Federal codes and standards, it has become more expensive to maintain the same level of energy savings as was achieved during the early days of lighting programs. That is exactly what the IRP is designed to model - the optimal resource mix given the respective costs for each of the options.

**Q. Page 30 of CAC witness Sommer’s Attachment AS-2, states that she is “unaware of any other utility” that uses Itron’s SAE load forecast methodology and then applies a degradation adjustment to their load forecast. Did any other Indiana utilities participate in I&M’s IRP stakeholder meetings and offer comments on I&M’s degradation approach?**

**A.** Yes. As documented in the Meeting Notes from the 2<sup>nd</sup> Stakeholder meeting<sup>13</sup>, a representative from Indianapolis Power & Light (IPL) mentioned that “SAE data captures naturally occurring energy efficiency in the market and that the Company

<sup>12</sup> Case No. U-20359 Rebuttal testimony of Chad M. Burnett, pg. 23.

<sup>13</sup>

<https://www.indianamichiganpower.com/global/utilities/lib/docs/info/projects/IMIntegratedResourcePlan/IMStakeholderMtg2Notes4-11-2018.pdf>

1 [IPL] has to calibrate or adjust for that”. In response to IPL’s comment, the  
2 Company said, “That is what I&M is trying to do.”

3 Furthermore, Attachment CMB-2R is a white paper that was published by  
4 Itron in 2010 which reiterates the need for an additional adjustment to the DSM  
5 savings assumptions when modeling within the SAE framework. Specifically, it  
6 states, “Because DSM impacts are embedded in the SAE framework, we must  
7 consider how to modify the SAE framework to account for historic and future  
8 DSM”.<sup>14</sup> This explains why the Company uses the degradation approach to DSM  
9 savings in the load forecast.

10 Finally, slide 13 of Attachment CMB-1R cites a 2017 study by The Brattle  
11 Group which surveyed a number of utilities in 2013 and again in 2016 to  
12 understand how utilities are modeling the impact of DSM in their load forecasts. It  
13 found that “SAE model[s have] gained popularity among utilities especially for long-  
14 term forecasting” and that “More utilities [13%] adopted mixed approaches” similar  
15 to I&M’s approach of modeling DSM in load forecasts.<sup>15</sup> This refutes the assertion  
16 on page 30 of Attachment AS-2 that I&M’s approach is “non-standard”.  
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<sup>14</sup> Pg 4 of Attachment CMB-2R.

<sup>15</sup> Slides 25-26 of ‘Estimating the Impact of DSM on Energy Sales Forecasts: A Survey of Utility Practices’ by Z. Wang, A. Faruqui, and J. Hall. The Brattle Group © 2017. [http://files.brattle.com/files/5648\\_estimating\\_the\\_impact\\_of\\_dsm\\_on\\_energy\\_sales\\_forecasts.pdf](http://files.brattle.com/files/5648_estimating_the_impact_of_dsm_on_energy_sales_forecasts.pdf)

1   **Q.   Beginning on page 8, CAC witness Sommer asserts that I&M's degradation**  
2       **factors as applied to a residential water heating rebate are "entirely**  
3       **inconsistent with how free ridership would affect savings for most energy**  
4       **efficiency programs." What are some of the issues that you found with this**  
5       **portion of Ms. Sommer's testimony?**

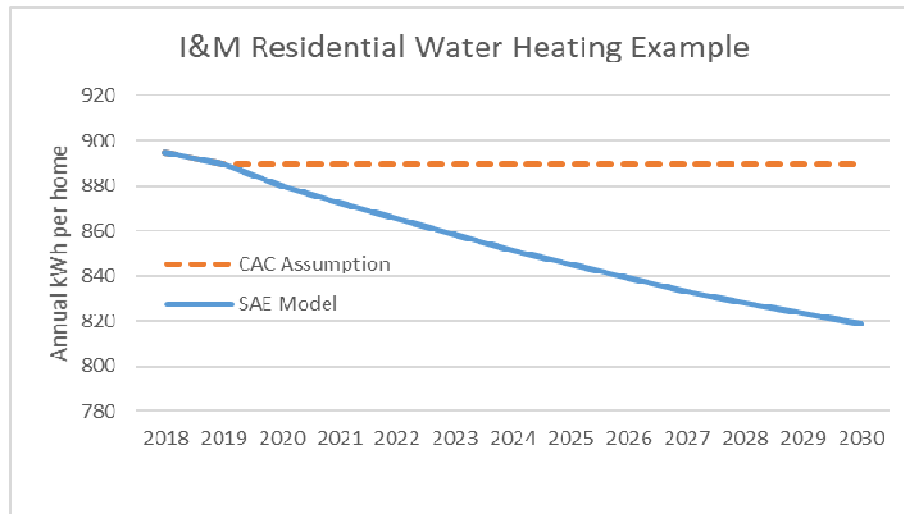
6   **A.**   Ms. Sommer's direct testimony (at 9) describes an example of a residential water  
7       heating measure with a 10-year life. She correctly points out that the degradation  
8       matrix is attributing less savings to each additional year. However, she neglects to  
9       mention that the saturations and efficiencies of residential heating technologies in  
10      the market are also changing.

11           Ms. Sommer's description of how free-riders would play into the load  
12      forecast methodology in this example does not accurately describe how the SAE  
13      models are accounting for energy efficiency over time. She states (p. 9) that "[i]f a  
14      customer participates in a program and takes a rebate for a new water heater, they  
15      are either a free rider or they are not. Their savings either persist - unchanged - for  
16      the entirety of the water heater life, or they are zero for the entirety of the water  
17      heater life."

18           The Company's load forecast models, however, already assume a  
19      significant improvement in efficiencies for water heating before making any  
20      adjustment for I&M's DSM/EE programs. Figure CMB-2R below shows the  
21      forecast of water heating consumption from the SAE model before making any  
22      adjustments for any DSM program. Through 2030, the SAE model is assuming

water heater usage declines at an average rate -0.7% per year.

**Figure CMB-2R**



**Q How does Ms. Sommer's failure to recognize the declining consumption forecast from the SAE model affect her criticism of the degradation approach?**

A. Ms. Sommer ignores this important detail when describing how she thinks the Company should model a rebating efficiency program. On page 8 of her testimony she states the savings estimate for a rebate program would be compared to "the standard new, less-efficient appliance the customer would otherwise have purchased - not the old appliance the customer is replacing and not a new appliance with efficiency lower than the minimum federal standard" (emphasis in original).

Figure CMB-2R above shows how the CAC's assumption for a water heating program in 2019 would compare to what is in the SAE model. If the SAE forecast model for water heating usage aligned with the CAC assumption described

1 by Ms. Sommer, the degradation adjustment may not be necessary. However, the  
2 CAC assumption does not align with the assumed efficiency gains in the SAE  
3 models and therefore the Company makes a degradation adjustment to the  
4 estimated DSM savings to prevent the double counting of energy efficiency in the  
5 load forecast.

6 **Q. Ms. Sommer (at 5) refers to Attachment AS-2 as having her entire analysis of**  
7 **concerns with I&M's approach to modeling DSM in the load forecast. On**  
8 **page 30 of Attachment AS-2, footnote 44 refers to a presentation from I&M's**  
9 **2<sup>nd</sup> IRP Stakeholder Meeting held April 11, 2018. What was the purpose of the**  
10 **presentation given at the April meeting and did it address any of the**  
11 **degradation issues raised by Ms. Sommer in this proceeding?**

12 **A.** The purpose of the second stakeholder meeting was to describe in great detail how  
13 the Company modeled DSM/EE assumptions in the IRP. Most of the issues raised  
14 in Ms. Sommer's direct testimony here were addressed in that meeting. I have  
15 attached the slide deck from that meeting as Attachment CMB-1R.

16 Ultimately, the real issue between Ms. Sommer's view of how DSM/EE  
17 savings should be modeled in an IRP compared to the Company's approach  
18 comes down to a measurement issue. There is a distinction between the way  
19 DSM/EE savings are "measured" and the way the historical actual sales are  
20 "metered" that go into the load forecast models.



1   **Q.    Can you elaborate on what you mean by the difference between ‘metered’**  
2       **and ‘measured’ savings?**

3    A.    The ‘metered’ input data that the load forecast models utilize come directly from  
4       customer meters. Similarly, the system load data that is used in the peak demand  
5       models come from the meters at the generators, tie-lines, etc. Everything is based  
6       on actual readings from a meter.

7           DSM/EE savings are not metered in the same way, but rather measured  
8       based on market potential studies, the EM&V process, and administrative  
9       adjustments. In fact, I&M could offer the exact same DSM/EE program in Michigan  
10      and Indiana, and it would likely be measured differently in each jurisdiction. For  
11      example, in Michigan, I&M’s DSM savings may include a stipulated bonus that may  
12      not exist in Indiana. According to MPSC Staff witness Gould in Case No. U-20359,  
13      “there are things that the Company can do that would earn them ‘stipulated savings’  
14      based on dollars spent, such as education for their customers or pilot programs,  
15      which test new and innovative measures for possible inclusion in future EWR  
16      programs...” or even a ‘multiplier’ that was offered to the Company for “rebating  
17      LED lightbulbs rather than CFLs” that “do not generate actual kWh sales reductions  
18      for the Company.”<sup>16</sup>

19           In addition to the stipulated savings measurement issue, there is also the  
20      issue of net-to-gross savings. As documented in Attachment AS-2 in response to a  
21      stakeholder question:

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<sup>16</sup> Direct testimony of Staff witness Karen M. Gould in Case No. U-20359, pgs. 4-5.

1 The baseline projection from the market potential study does include  
2 some estimate for the impact of existing and approved changes to  
3 building codes and appliance standards but does not account for free  
4 ridership and spillover that result from I&M programs. The market  
5 potential study does, however, apply a net-to-gross ratio (similar in  
6 concept to the degradation factor) when translating from a measure-  
7 level to a program-level. The IRP inputs are at the measure level  
8 which have not been adjusted for free riders and spillover. Therefore  
9 the measure level inputs from the MPS are degraded in the IRP  
10 modeling so that the output from the IRP can be consistent with the  
11 program level outputs, both at a net savings level.<sup>17</sup>

12 If the Company did not apply the degradation matrix to the gross measure level  
13 savings from the market potential studies, as CAC recommends, it would create a  
14 mismatch in the IRP modeling whereby the DSM savings would be overstated from  
15 what is actual and verified and the resulting load forecast for capacity requirements  
16 would be understated. In other words, if I&M followed CAC's modeling advice,  
17 there is greater risk that I&M would not adequately plan for the actual reserve  
18 requirement that will be needed.

19 **Q. Do you agree that CAC's revised approach to modeling DSM savings**  
20 **(Corrected CAC Exhibit 2, Attachment AS-2 at 32) would have been "far more**  
21 **accurate"?**

22 **A.** No. Ms. Sommer offers no evidence to support the claim that CAC's approach  
23 would improve the accuracy of the forecast. In her revised testimony in Attachment  
24 AS-2 at page 32, Ms. Sommer now recommends I&M should "create a DSM  
25 forecast that does not include any forward going utility-sponsored efficiency  
26 savings, and then model the savings from prior installed measures that persist past  
27 2018 as a load modifier, if necessary". If read literally, this suggests that CAC has

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<sup>17</sup> Attachment AS-2, page 34.

1 changed its position and no longer believes the Company should promote utility-  
2 sponsored DSM programs going forward.

3 If one were to assume that she intended to recommend a “load forecast”  
4 procedure rather than a “DSM forecast” procedure, her new recommended  
5 modeling approach would align with I&M’s approach for the load forecast that was  
6 used as an input in the IRP process as described on slide 26 of Attachment CMB-  
7 1R. As the Company explained to stakeholders at the April 11, 2018 meeting, “the  
8 load forecast that goes into the IRP modeling only includes the impact of current  
9 filed programs over their expected measurement life.” “The long-term EE/DSM  
10 savings impacts are solved for as part of the IRP modeling [process].”

11 Since Ms. Sommer’s revised testimony now aligns with the Company’s load  
12 forecast methodology for the IRP, her original critiques of the Company’s approach  
13 are in conflict with her revised position.

14 **Q. Would it be appropriate to eliminate future utility-sponsored DSM programs**  
15 **as Ms. Sommer’s revised testimony could be read to suggest without a**  
16 **directive from the IURC?**

17 A. No. Ms. Sommer does not provide an explanation for why she thinks it would be  
18 more accurate to assume no utility-sponsored DSM programs in the future.  
19 Perhaps she is assuming the IURC will follow the example of a number of other  
20 state utility Commissions that have recently suspended some or all utility-  
21 sponsored DSM programs in their respective states. In fact, two of I&M’s sister

operating companies<sup>18</sup> within the AEP portfolio, Ohio Power Company and Kentucky Power Company, have recently been instructed to suspend promoting future DSM programs.

Without a Commission directive to suspend DSM programs moving forward, I&M felt it was reasonable and appropriate to include future DSM programs as part of the Company's Preferred Plan of resource options to satisfy its load obligations. I&M witness Fisher addresses how the IRP models select future energy efficiency levels.

**Q. Ms. Sommer also claims (at 7) the Company did not need to apply a degradation adjustment to the DSM savings in the load forecast because “naturally occurring savings were already netted out of the market potential study estimate of savings potential.” How do you respond?**

**A.** There are a couple of issues that should be clarified. First, the estimate of “naturally occurring savings” from the MPS is not necessarily in sync with the trends in appliance saturations and efficiencies that are used in the load forecast. According to the AEG report, “the end-use projection [in the market potential study] includes the relatively certain impacts of codes and standards that will unfold over the study timeframe” and the mandates were defined as of December 2015.<sup>19</sup> The Company's SAE models are updated annually to capture the latest projections from

<sup>18</sup> Ohio Power Company in Ohio Rev. Code Sec. 4928.66.(F) (2019) and Kentucky Power Company in Case No.2017-00097.

<sup>19</sup> Pg 15 of Applied Energy Group (AEG) Indiana Michigan Power Company Energy Efficiency Market Potential Study  
<https://www.indianamichiganpower.com/global/utilities/lib/docs/info/projects/IMIntegratedResourcePlan/IMReport-ExecutiveSummaryFinal6-2-16.pdf>

1 the Energy Information Administration (EIA) 2018 Outlook for legislated efficiency  
2 codes and standards. Similarly, the market potential study used I&M's 2016  
3 Residential Appliance Saturation Survey. The Company's load forecast for the  
4 2018-19 IRP incorporated the results of I&M's 2019 Residential Appliance  
5 Saturation Survey. Since the load forecast is developed each year and is able to  
6 capture more recent updates to input assumptions such as the saturations and  
7 efficiency projections of what is happening in the market, the estimate of 'naturally  
8 occurring efficiency' in the SAE models may differ from what was estimated in the  
9 MPS.

10 Even if the MPS used the same assumptions for naturally occurring  
11 efficiency as the SAE models, the Company's degradation adjustment would still be  
12 appropriate. As mentioned above, the MPS applies a net-to-gross ratio when  
13 translating from a measure-level to a program-level. Since the IRP modeling inputs  
14 from the MPS are at a measure level, they would not have already included the net-  
15 to-gross adjustment as Ms. Sommer suggests and would still be at a gross level  
16 (which includes free-riders, spillover, etc.). The degradation adjustment is needed  
17 to prevent the double counting of energy efficiency in the load forecast. I&M  
18 witness Cottrell's rebuttal explains why the MPS remains useful as a realistic  
19 assessment of the energy efficiency savings potential for the Company.

1 **Q. Can you give some specific examples of how the appliance saturations**  
2 **changed between the 2016 Residential survey and the 2019 survey that might**  
3 **impact the estimate of potential DSM savings available?**

4 A. Yes. The change in the saturation of lighting technologies is probably the easiest  
5 example. In I&M's Residential Appliance Saturation Survey, the Company asks  
6 customers what is the main source of lighting in various rooms in their homes. In  
7 the 2016 survey that was used by AEG in the development of their market potential  
8 study, 56% of lighting was still using incandescent bulbs while only 12% of lighting  
9 was using LED bulbs. In the 2019 survey, however, which is what the Company's  
10 load forecast was calibrated to, the saturation of incandescent light bulbs had fallen  
11 to 35% while the saturation of LED lighting increased to 35%.

12 The fact that the load forecast is based off of more recent assumptions that  
13 recognize the adoption for more efficient lighting has accelerated significantly from  
14 what was provided in the market potential studies is another reason why it is  
15 important and appropriate for the company to apply a degradation factor to DSM  
16 programs before making an adjustment to the load forecast results that already  
17 account for energy efficiency.

18 **Q. Could you summarize what is wrong with Ms. Sommer's interpretation of the**  
19 **Company's approach to modeling DSM/EE savings in the IRP and explain**  
20 **why you are confident in the Company's approach?**

21 A. Yes. The majority of CAC's critique of the Company's approach to modeling DSM  
22 savings in the IRP has to do with the way I&M calibrates the DSM savings

1 assumptions with the energy efficiency that is already embedded in the SAE load  
2 forecast models. What Ms. Sommer described as a 'fatal flaw' is actually standard  
3 practice that is used by other utilities that employ the SAE modeling framework and  
4 has been accepted by various regulatory commissions across the country including  
5 those in Indiana and Michigan. Furthermore, after revising her testimony, Ms.  
6 Sommer now recommends an approach that appears to be similar to what the  
7 Company actually did in the IRP which suggests her critique of the Company's  
8 approach was overstated.

9 The Company's load forecast methodology, which includes its modeling of  
10 DSM/EE savings, has proven to produce accurate and reliable projections that  
11 are useful for planning and setting rates. As a result, the Commission should  
12 reject CAC's recommendation and accept the Company's modeling of DSM  
13 savings in the IRP as reasonable.


14 **Q. Does this conclude your pre-filed rebuttal testimony?**

15 **A.** Yes it does.

**VERIFICATION**

I, Chad M. Burnett, Director of Economic Forecasting of American Electric Power Service Corporation (AEPSC), affirm under penalties of perjury that the foregoing representations are true and correct to the best of my knowledge, information, and belief.

Date: 3/1/2020

  
Chad M. Burnett





# 2018 Integrated Resource Plan Stakeholder Workshop #2

April 11, 2018

Barnes and Thornburg, LLC  
11 S. Meridian St.  
Indianapolis, IN 46204



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I&M Internal: 8-237-6338  
Toll Free: 1-877-253-4307  
Passcode: 223596#



## GROUND RULES

### Ground Rules

- Everyone will be heard and have the opportunity to contribute
- Please be respectful of all opinions and/or proposals
- Stick to the time allotted

### Housekeeping

- Safety – emergency exits
- Restroom locations
- Lunch logistics
- Please silence phones and if you must take a call, please step outside the room to do so



## I&M's Key Priorities for the 2018 IRP

- ✓ Stakeholder Engagement
- ✓ Continuous Improvement of IRP Processes
- ✓ Continued DSM/EE Advancement/Deployment
- ✓ Continued Renewables Deployment
- ✓ Continued Support for CHP and DG Opportunities
- ✓ Understanding of Rockport Disposition Options
- ✓ Develop a reasonable preferred resource plan that balances multiple factors such as cost effectiveness, reliability, portfolio risk and uncertainty to meet the future energy and capacity needs of I&M's customers
- ✓ Develop an IRP that meets the requirements of 170 IAC 4-7 (IURC draft proposed rule) and MCL 460.6t(4)



## Goals for Today

### □ Today's Goals:

- ✓ Discuss DSM/EE impacts on the Load Forecast
- ✓ Discuss preliminary DSM/EE IRP Inputs
- ✓ Discuss preliminary IRP Assumptions and Portfolios



## Follow-up Steps in the Stakeholder Process

Meeting	Date	Topic
1	February 15, 2018 Northeast Indiana Innovation Center 3211 Stellhorn Road Fort Wayne, IN 46815	2018 IRP Kick-off Meeting - Stakeholder Process & Scenario Discussion
2	April 11, 2018 Barnes & Thornburg 11 S. Meridian St. Indianapolis, IN 46204	Considerations for Modeling DSM in the 2018 IRP & Update on the IRP
3	August 1, 2018 I&M South Bend Service Center 2929 Lathrop St. South Bend, IN 46628	Final Inputs, Portfolios, Scenarios & Initial Modeling Results
4	Sept. - Oct. 2018	Modeling Results & Preferred Portfolio Discussion

In addition to the four stakeholder workshops, teleconference discussions may be held as needed



## Stakeholder Comments

- ☐ I&M has added a comment form on its webpage  
<https://www.indianamichiganpower.com/info/projects/IntegratedResourcePlan>
- ☐ Please submit all comments, suggested inputs, portfolio scenarios, critique, etc. as soon as you can so I&M will have time to consider your input. Refer to slide 55 for a summary of upcoming stakeholder input due dates
- ☐ Specifically, I&M welcomes comments on:
  - Fundamental Commodity Forecast Pricing Assumptions
  - Load Forecast
  - Cost of Technology Options
  - DSM/Energy Efficiency assumptions
  - Sensitivity cases
  - Portfolios to Consider
  - Other
- ☐ I&M will continue to post stakeholder meeting minutes and comments received through the website





## Today's Agenda

- ☐ Opening Remarks
- ☐ DSM Impacts on the Load Forecast
- ☐ Developing DSM Inputs for the IRP
- ☐ Next Steps for DSM Input Development
- ☐ Preliminary IRP Assumptions and Portfolios
- ☐ Next Steps





## Today's Agenda

- ☒ Opening Remarks
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## Energy Efficiency

- ☐ I&M's existing programs and underlying technologies have performed well
- ☐ I&M expects to evolve the next generation of programs consistent with the IRP
- ☐ Achieving incremental savings will be challenged by the elimination of low-hanging fruit and increasing efficiency baselines



## Today's Agenda

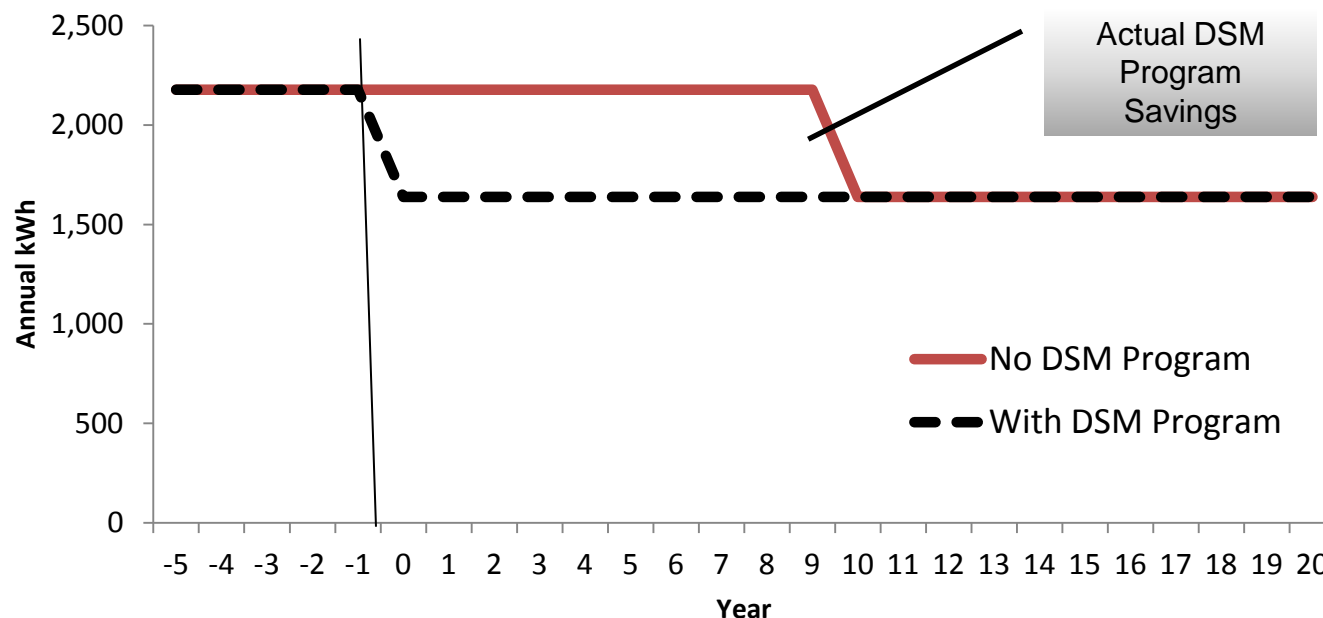
- ☐ I&M's DSM Performance & Existing Programs
- ☒ **DSM Impacts on the Load Forecast**
- ☐ Developing DSM Inputs for the IRP
- ☐ Next Steps for DSM Input Development
- ☐ Preliminary IRP Assumptions and Portfolios
- ☐ Next Steps



## Accounting for DSM in the Load Forecast

The purpose or effect of the Company's DSM/EE programs is to accelerate the adoption of energy efficient technology to enable our customers to be more efficient consumers of energy.

### Cooling EE/DSM Program Example



*Example: The J Doe family replaced their HVAC system 5 years ago with a SEER 13 system. Since then, the industry has introduced more efficient (SEER 15) units. 10 years from now, J. Doe will have to replace the system with whatever is available in the market at that time (SEER 15). Today, the utility offers an incentive to help J. Doe replace his HVAC system now with a SEER 15 and begin saving energy immediately.*



## Multiple Approaches to Modeling DSM Impacts on Load Forecast

- The Brattle Group<sup>1</sup> has identified 6 different approaches used across the industry to model DSM impacts in energy sales forecasts.

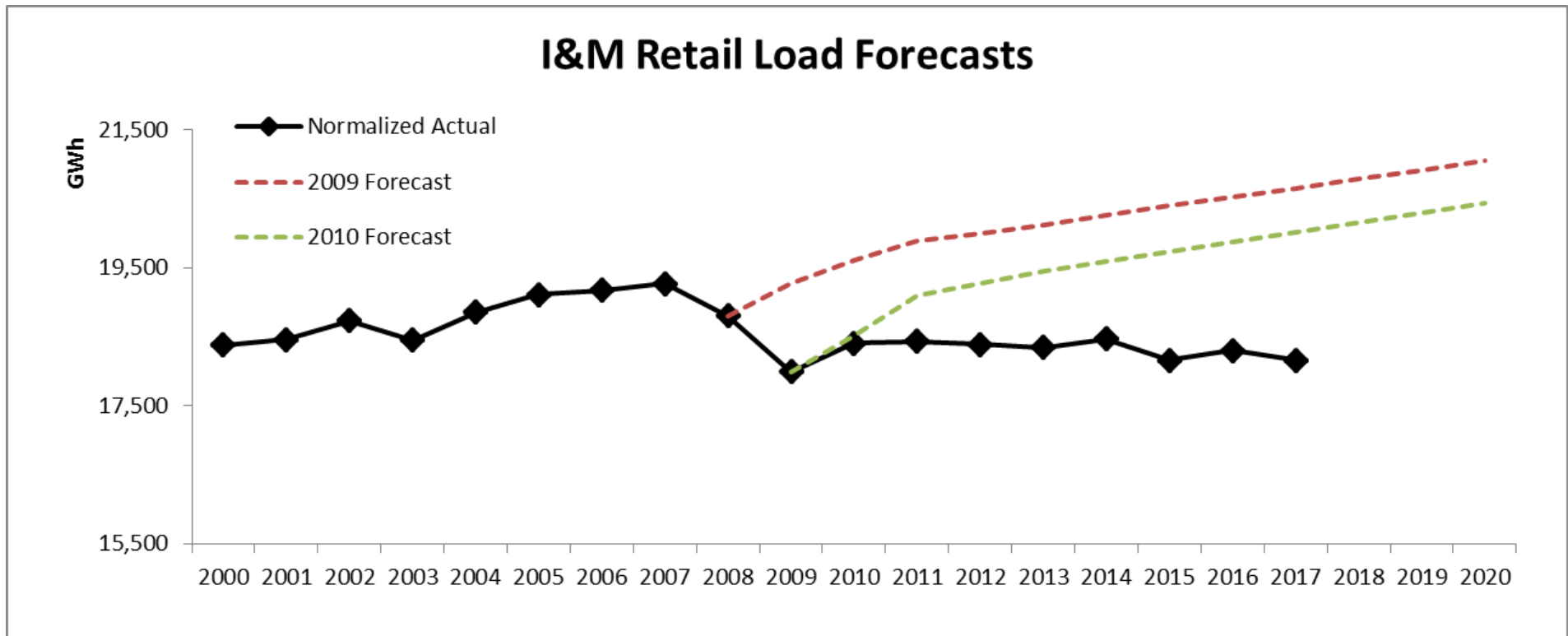


1. DSM Already Embedded in Sales Data - No post-regression adjustment needed
  2. **Historical DSM Embedded in Sales Data - Adjust for incremental DSM in forecast**
  3. Reconstruct Historical sales as if no DSM and do post-regression adjustment
  4. Include DSM activities as a right-hand side variable in econometric models
  5. **Hybrid Model (SAE) that embeds end-use features in econometric models**
  6. **Combination of approaches identified above**
- I&M's approach has evolved over the years but is most like #6, Combination of Approaches #5 and #2.

<sup>1</sup> 'Estimating the Impact of DSM on Energy Sales Forecasts: A Survey of Utility Practices' by Z. Wang, A. Faruqui, and J. Hall. The Brattle Group. 2017  
[http://files.brattle.com/files/5648\\_estimating\\_the\\_impact\\_of\\_dsm\\_on\\_energy\\_sales\\_forecasts.pdf](http://files.brattle.com/files/5648_estimating_the_impact_of_dsm_on_energy_sales_forecasts.pdf)



## The Evolution of Modeling DSM Impacts in the Load Forecast

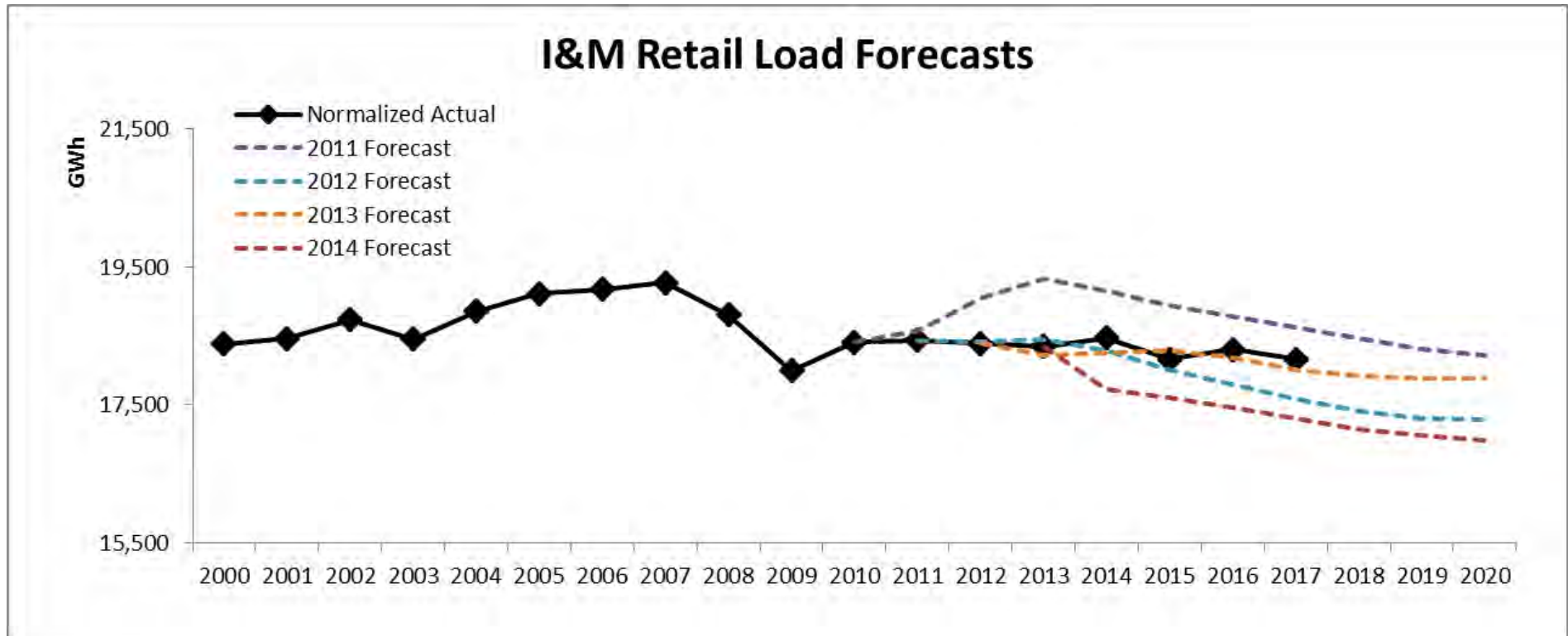


When I&M initially started their DSM/EE programs in 2008, it was expected that the programs would only have a minor impact on overall load growth. (*The modeling of DSM at that time was similar to The Brattle Group's #5 approach.*)





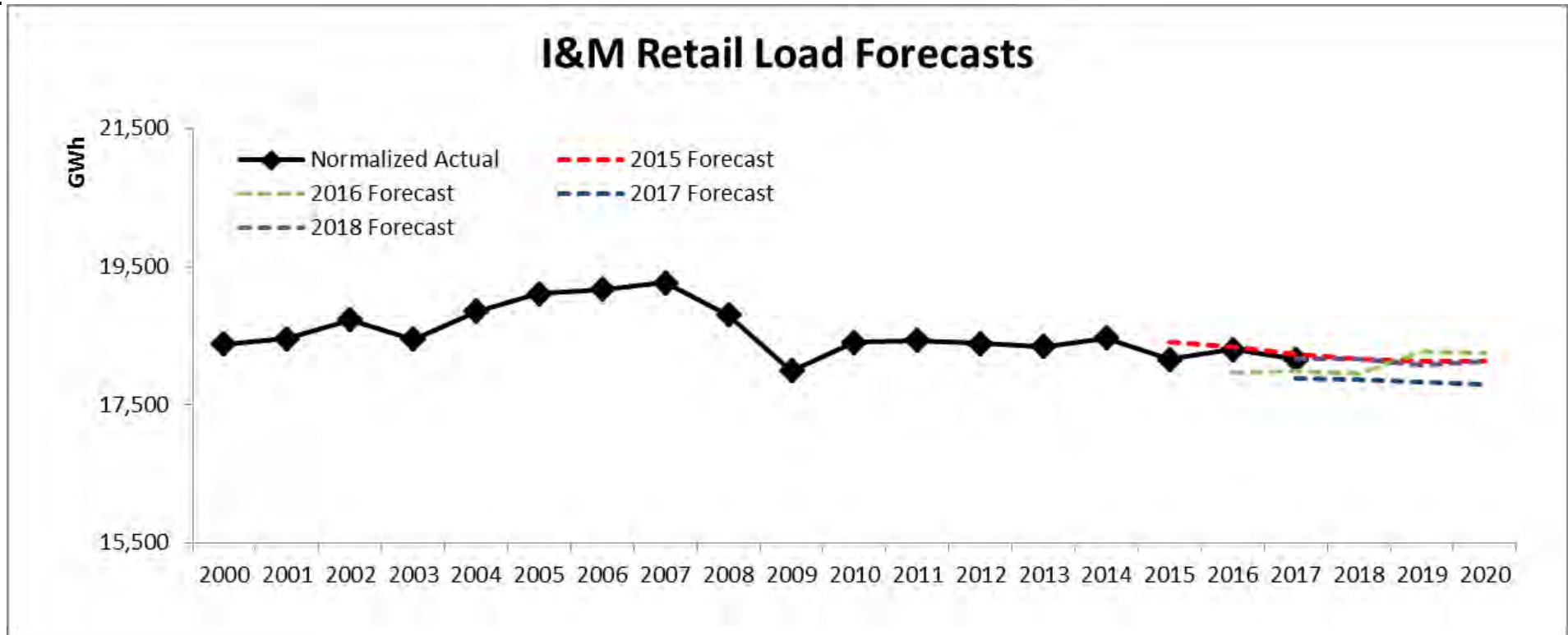
## The Evolution of Modeling DSM Impacts in the Load Forecast



The DSM assumptions increased significantly in the 2011-14 forecast vintages which had a dramatic impact on the load forecast. (*The modeling during this time was more similar to The Brattle Group's #2 approach.*)



## The Evolution of Modeling DSM Impacts in the Load Forecast



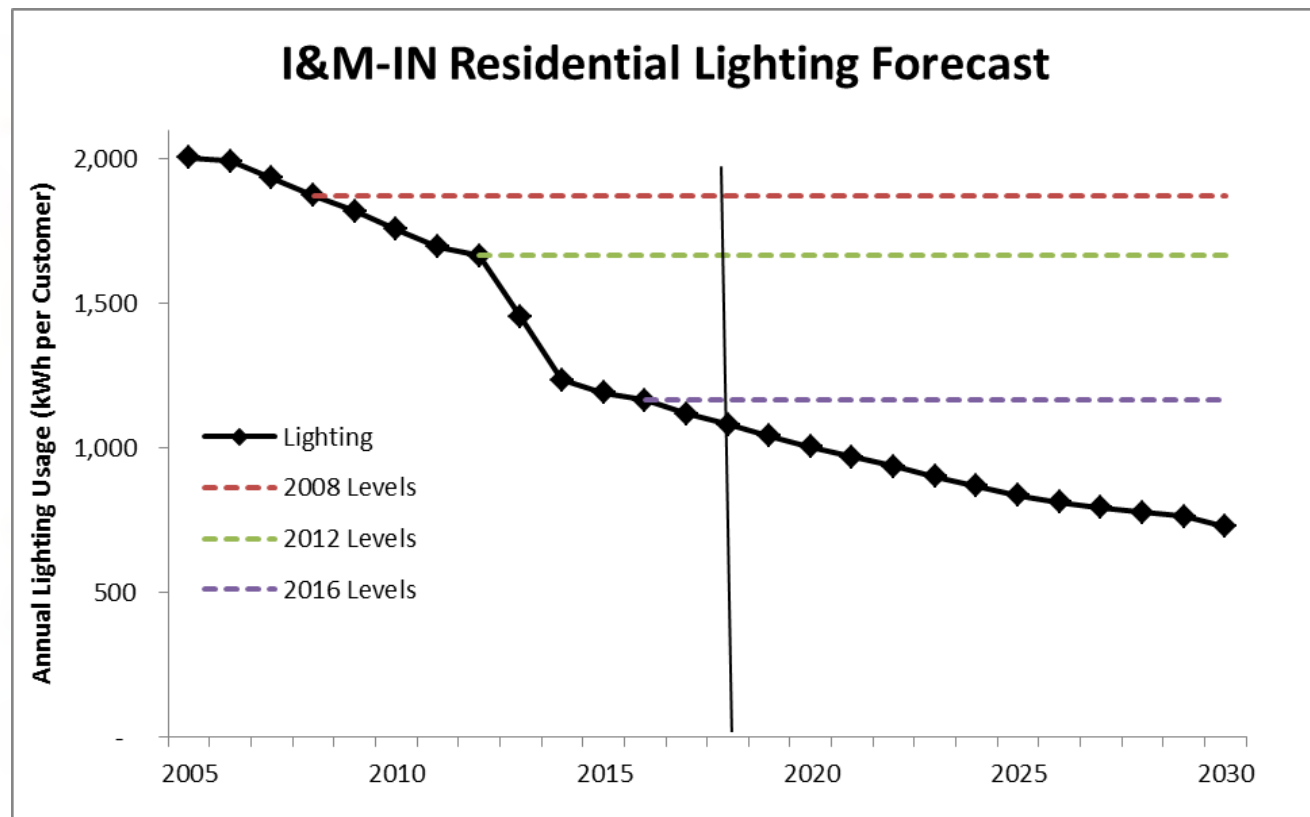
I&M has been using the current approach to modeling DSM program impacts (The *Brattle Group's #6 approach*) since the 2015 Forecast which has resulted in better alignment between the forecast and the actual results.





## Accounting for DSM in the Load Forecast

The way DSM program savings are measured (historical base) is different than the way DSM program savings are modeled (forecast).





## I&M's Recipe for Including DSM Program Impacts in Load Forecast

### Ingredients:

- Historical EE/DSM Program Savings
- Filed EE/DSM Program Savings by Program
- IRP DSM Savings from Preferred Portfolio
- Pre-adjusted SAE load forecast
- End-use Load Shapes
- Degradation Matrix

### Directions:

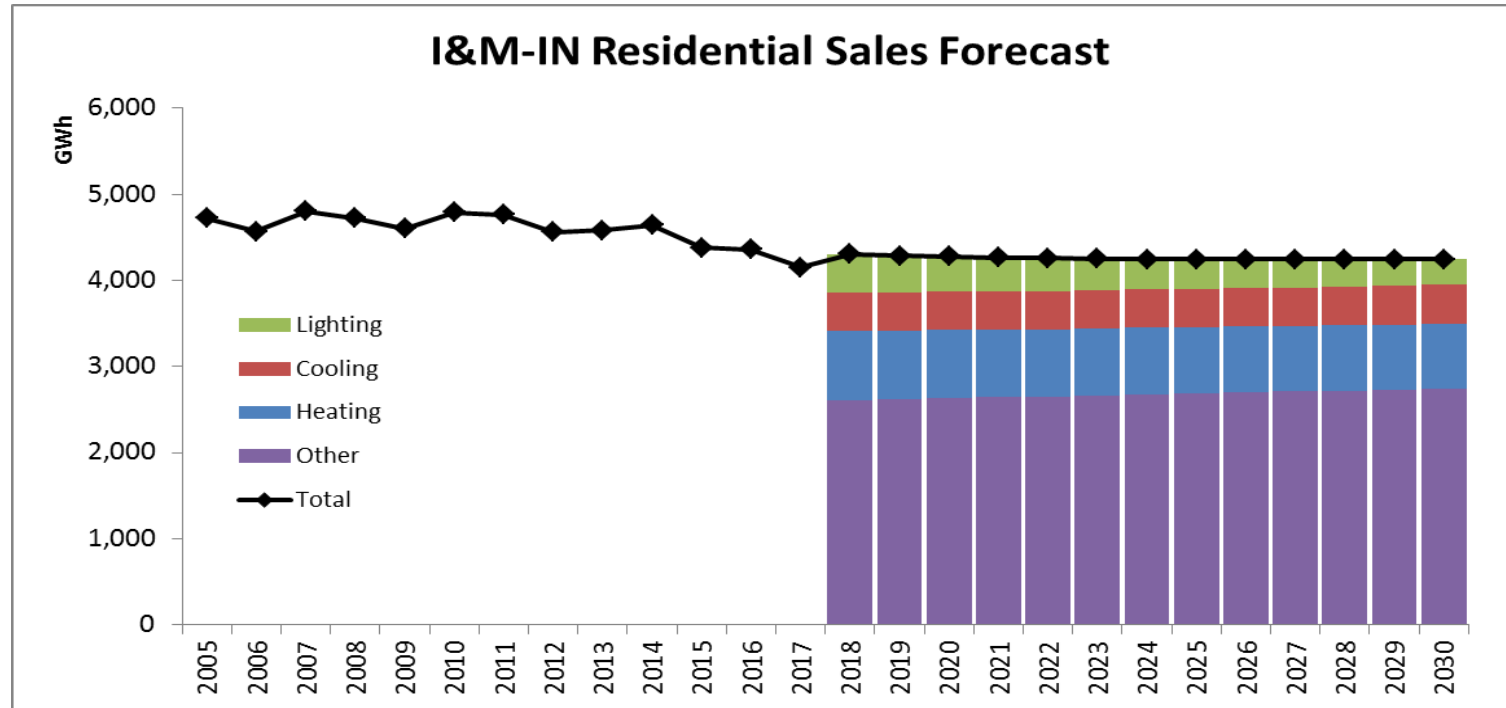
- Start with SAE load forecast before DSM adjustments. Set aside for later.
- Map the specific EE/DSM programs to class and end-use (i.e. Residential Lighting, Commercial Cooling) to match up with the respective load shapes.

### Directions: (cont....)

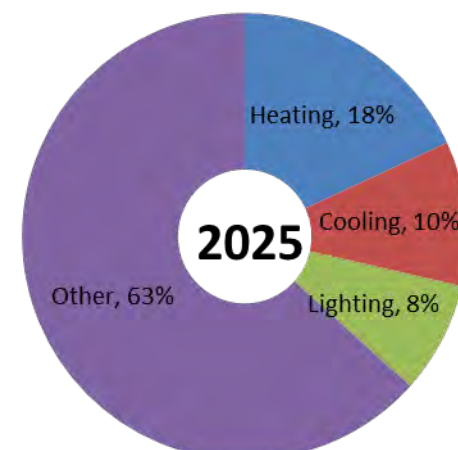
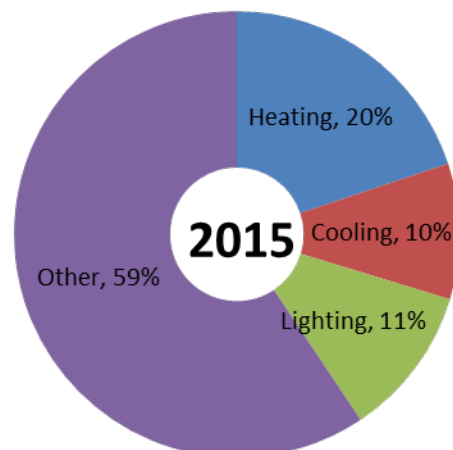
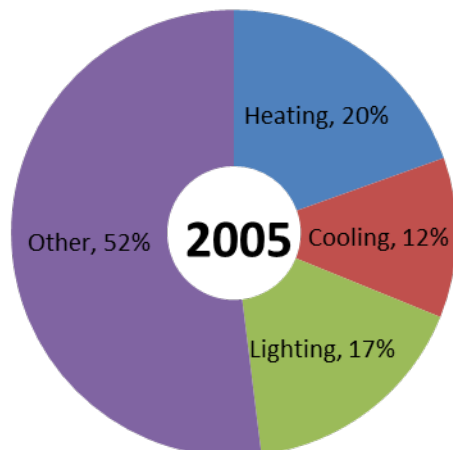
- Assign a measurement life for each EE/DSM program that will be used in the degradation matrix (10 year, 15 year, etc.)
- Shift the annual savings by  $\frac{1}{2}$  year to account for the fact that not all program savings reported in a specific year will be installed and functioning for the entire calendar year.
- Insert each year's annual EE/DSM program savings impact into Degradation Matrix and sum the output by end-use.
- Subtract the cumulative degraded DSM impacts by end-use from the original SAE forecast.



## SAE Model Approach



- ❑ The Statistically Adjusted End-use (SAE) approach accounts for efficiency trends and saturations by end-use category (i.e. heating, cooling, lighting, other).





## What Is Included in the SAE End-Use Categories

### Heating

- *electric furnace/ resistant space heaters, heat pump, ground-source heat pump, furnace fan, secondary heating*

### Cooling

- *central a/c, heat pump, ground source heat pump, room/ window a/c*

### Lighting

- *Lighting*

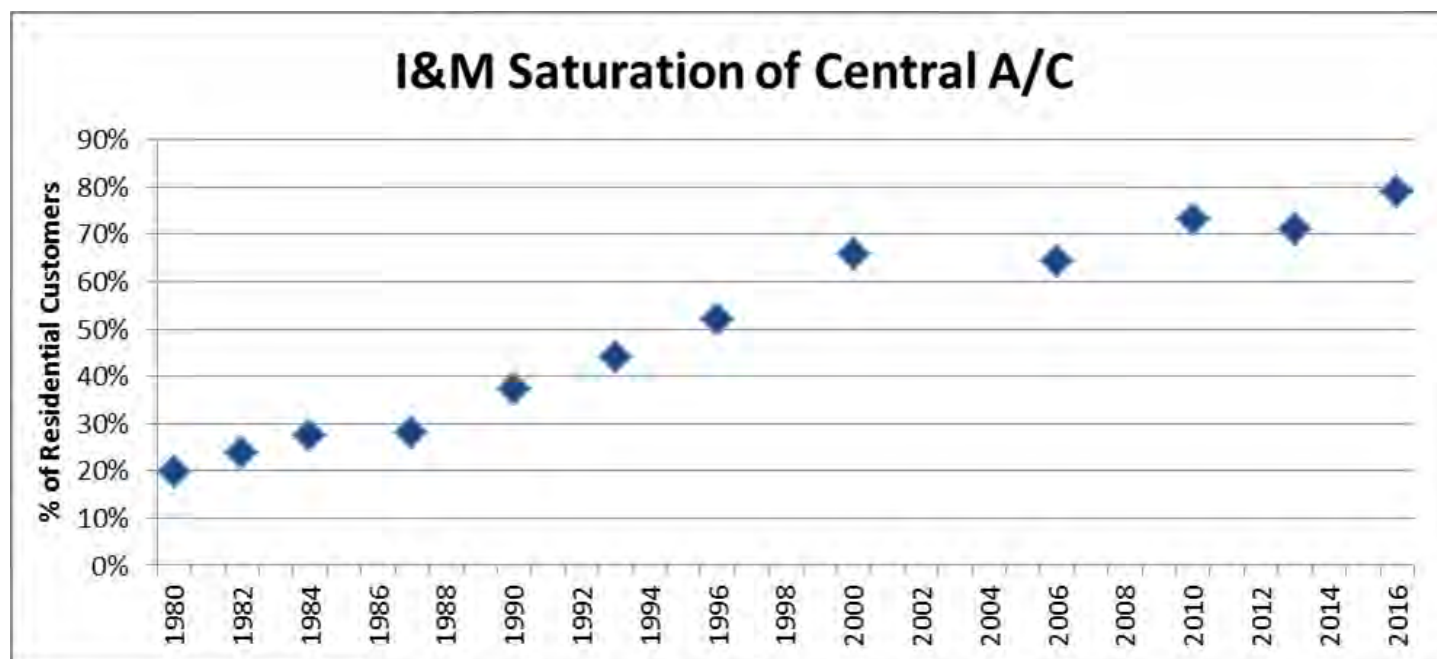
### Other

- *electric water heater, electric cooking, refrigerator, 2<sup>nd</sup> refrigerator, freezer, dishwasher, clothes washer, electric clothes dryer, television, miscellaneous electric appliances*



## Results from Residential Appliance Saturation Survey Use in SAE

- Since 1980, AEP's Economic Forecasting group has monitored the saturation trends and efficiencies of the various Residential end-use appliances in use within the AEP (I&M) service territory.
- The results are incorporated into the load forecasting process which supports the operating companies Resource Plan as well as their long term Financial Forecast.








## I&M-IN EE/DSM Program Mapping

Program Name	Heating	Cooling	Lighting	Other	Residential	Commercial	Industrial
Low/Moderate Income	16%	10%	11%	63%	100%		
Rebates			100%		100%		
Appliance Recycling			40%	60%	100%		
Whole House(home energy audit)			100%		100%		
URWP Loans				100%	100%		
Lighting Programs			100%		100%		
Home Energy Assessments	60%	40%			100%		
Income Qualified Weatherization	60%	40%			100%		
Home Energy Products	10%		90%		100%		
C&I - Rebates Prescriptive				100%		50%	50%
C&I - Incentives				100%		100%	
School Energy Education				100%	25%	75%	0%
Online Audit			100%		100%		
New Construction	60%	40%			100%		
Low Income Weatherization	60%	40%			100%		
Home Energy Reporting	60%	40%			100%		
Renewables & Demonstration				100%	100%		
C&I Custom	36%	64%				100%	
C&I HVAC Optimization /	36%	64%				100%	
C&I Direct Install (Audit)				100%		50%	50%
C&I Rebates				100%		80%	20%
C&I Load Management				100%		80%	20%
Res - Peak Reduction				100%	100%		
Internal Facility / EECO / Other (VVO)	60%	40%			50%	50%	

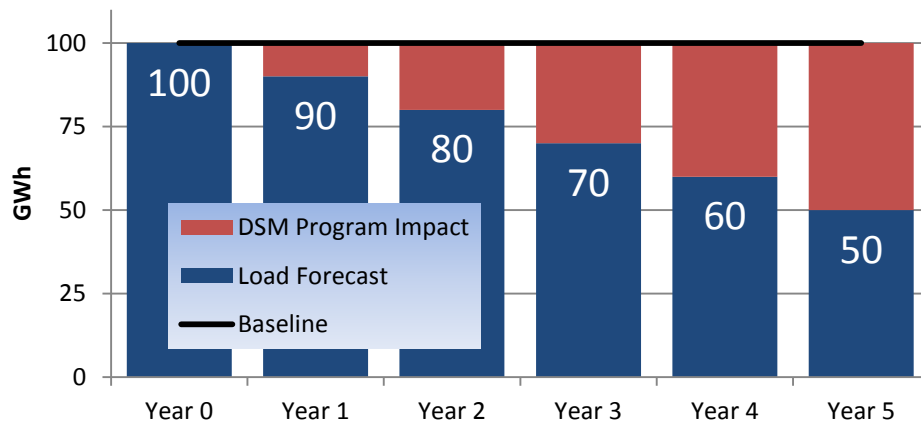
 Indicates programs that are included in I&M's most recent IN EE/DSM portfolio plan.



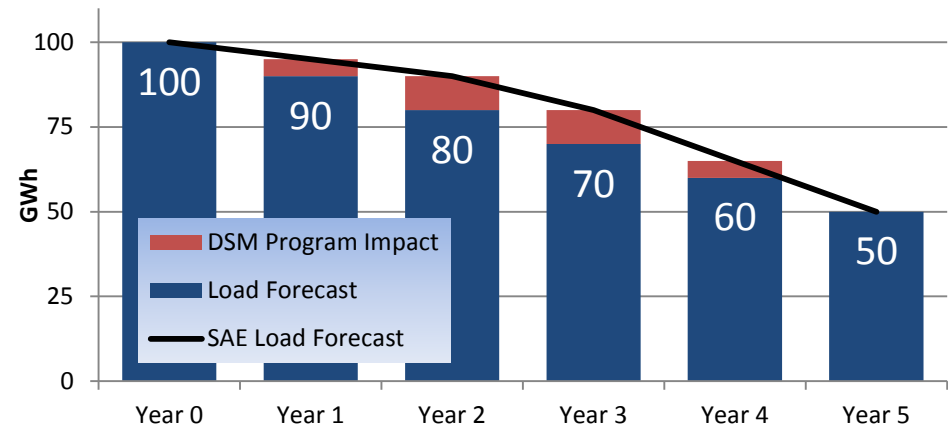
## Why Apply Degradation to DSM/EE Program Savings?

Since the 'actual' DSM/EE Program savings are measured against a historical base, and the SAE forecast models already account for the changing saturations and appliance efficiencies that are likely to occur in the market, we need to degrade the measured DSM/EE savings over time to keep from double counting the impact of the increased energy efficiency in the load forecast.

**DSM Savings if Load Forecast Models  
Don't Account for EE**



**DSM Savings When Load Forecast  
Models Do Account for EE**





## Degradation Matrix (Residential Heat Example)

	Residential Heat														
15	141,498	724,470	988,144	525,454	4,324,829	9,873,019	14,989,314	19,597,677	22,093,305	22,504,607	27,822,923	35,356,598	36,443,620	18,221,810	
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	
2008	141,498														
2009	131,459	724,470													
2010	120,314	673,069	988,144		Degraded impacts are summed by year to compute cumulative impacts										
2011	108,258	616,008	918,035	525,454											
2012	95,528	554,279	840,206	488,173	4,324,829										
2013	82,407	489,105	756,011	446,786	4,017,984	9,873,019									
2014	69,209	421,922	667,117	402,015	3,677,348	9,172,531	14,989,314								
2015	56,279	354,350	575,482	354,745	3,308,849	8,394,903	13,925,827	19,597,677							
2016	43,977	288,150	483,317	306,017	2,919,784	7,553,669	12,745,224	18,207,227	22,093,305						
2017	32,662	225,163	393,023	257,008	2,518,724	6,665,485	11,468,055	16,663,656	20,525,792	22,504,607					
2018	22,675	167,231	307,112	208,993	2,115,343	5,749,918	10,119,605	14,993,830	18,785,658	20,907,912	27,822,923				
2019	14,314	116,096	228,095	163,309	1,720,153	4,829,050	8,729,581	13,230,809	16,903,190	19,135,382	25,848,895	35,356,598			
2020	7,809	73,288	158,350	121,291	1,344,145	3,926,884	7,331,511	11,413,432	14,915,661	17,217,870	23,657,479	32,848,058	36,443,620		
2021	3,291	39,983	99,961	84,204	998,309	3,068,506	5,961,834	9,585,535	12,866,853	15,193,339	21,286,818	30,063,267	33,857,956	18,221,810	
2022	753	16,849	54,535	53,155	693,054	2,279,009	4,658,637	7,794,759	10,806,186	13,106,390	18,783,848	27,050,697	30,987,548	16,928,978	
2023		3,857	22,981	28,999	437,503	1,582,151	3,460,013	6,090,903	8,787,368	11,007,360	16,203,708	23,869,992	27,882,358	15,493,774	
2024			5,261	12,220	238,684	998,763	2,402,037	4,523,771	6,866,537	8,950,959	13,608,633	20,591,222	24,603,864	13,941,179	
2025				2,797	100,582	544,884	1,516,332	3,140,527	5,099,842	6,994,368	11,066,260	17,293,473	21,224,290	12,301,932	
2026					23,025	229,616	827,248	1,982,518	3,540,451	5,194,783	8,647,286	14,062,696	17,825,153	10,612,145	
2027						52,562	348,605	1,081,580	2,234,978	3,606,362	6,422,421	10,988,731	14,495,047	8,912,576	
2028							79,800	455,782	1,219,312	2,276,585	4,458,622	8,161,434	11,326,574	7,247,524	
2029								104,335	513,822	1,242,011	2,814,591	5,665,893	8,412,353	5,663,287	
2030									117,621	523,388	1,535,524	3,576,703	5,840,088	4,206,177	
2031										119,811	647,076	1,951,302	3,686,668	2,920,044	
2032											148,124	822,286	2,011,294	1,843,334	
2033												188,232	847,567	1,005,647	
2034													194,019	423,783	
2035														97,010	

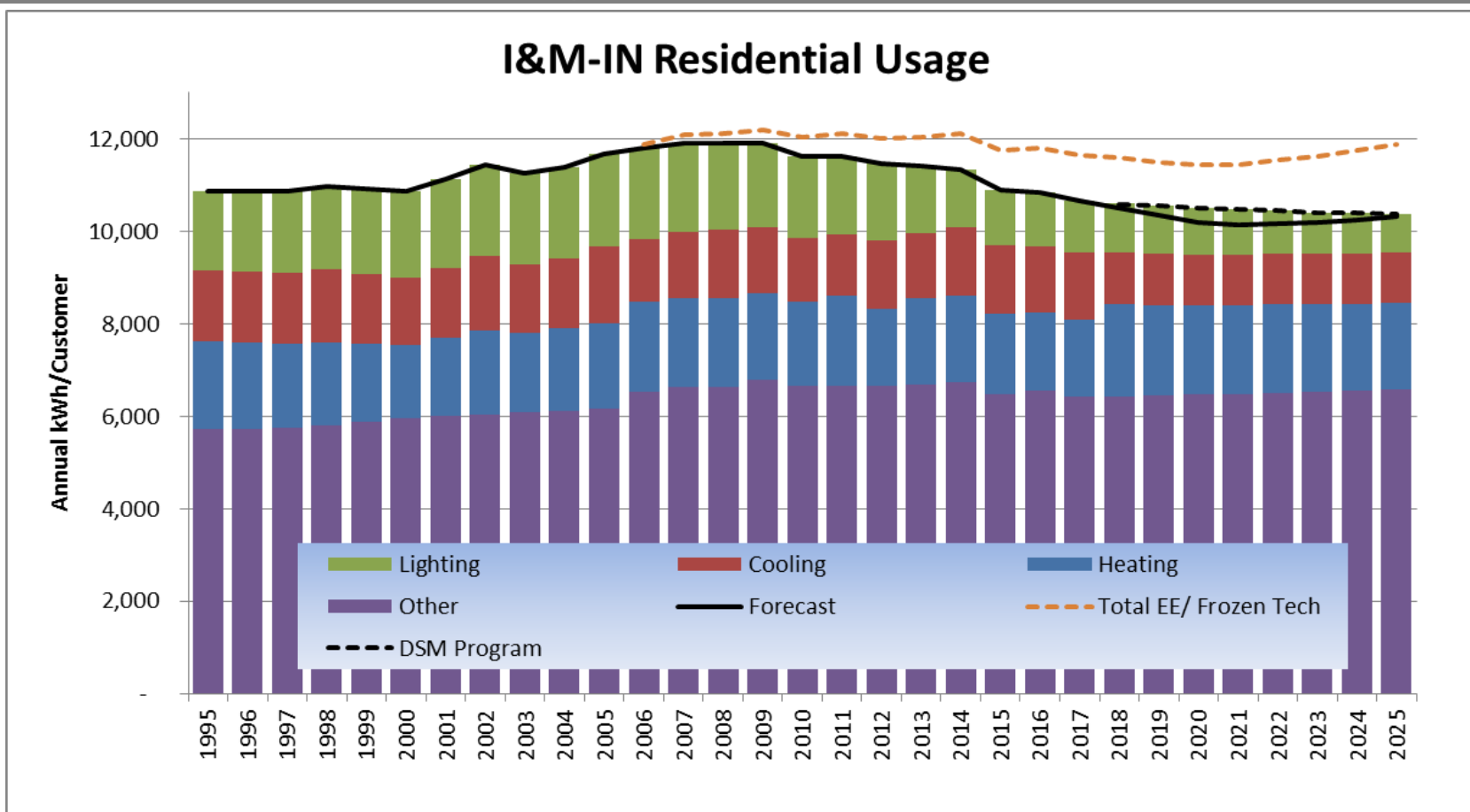
Degraded impacts are summed by year to compute cumulative impacts

Residential Heating programs are assumed to have a 15 year measure life. The savings from a specific year's program are input into the matrix and degraded over its expected measure life.





## Declining Residential Load Growth



- ☐ The bars represent the forecast by end use category.
- ☐ The Total EE line represents what the load forecast would be if all efficiencies and technology that existed in 2005 were held constant ('frozen') at those levels throughout the forecast horizon.
- ☐ The black forecast line dips below the stacked bars which represents the adjustment made to the load forecast for the incremental impact of the EE/DSM programs not already accounted for in the SAE models.



## DSM Assumptions Used in I&M's Load Forecast

### Load Forecast used in IRP Modeling

- ☐ Short term DSM assumptions taken directly from most recent filed/approved EE/DSM programs (usually a 3 year cycle)
- ☐ Long-term EE/DSM savings impacts are solved for as part of the IRP modeling. Therefore, the load forecast that goes into the IRP modeling only includes the impact of current filed programs over their expected measurement life.



## Today's Agenda

- ☐ I&M's DSM Performance & Existing Programs
- ☐ DSM Impacts on the Load Forecast
- ☒ **Developing DSM Inputs for the IRP**
- ☐ Next Steps for DSM Input Development
- ☐ Preliminary IRP Inputs, Assumptions and Portfolios
- ☐ Next Steps



## Developing DSM Inputs for the IRP

- **DSM/EE Development for the IRP**
  - **Energy Efficiency Resources**
    - Focus on 2016 Market Potential Study Overview & Recent Program Lessons Learned
    - Overview of IRP Bundle Development & Summary
      - Focus on Top Twenty MPS measures
      - Illustrative “EE Supply Stack”
  - **Demand Response Resources**
    - Existing Programs
    - New Programs



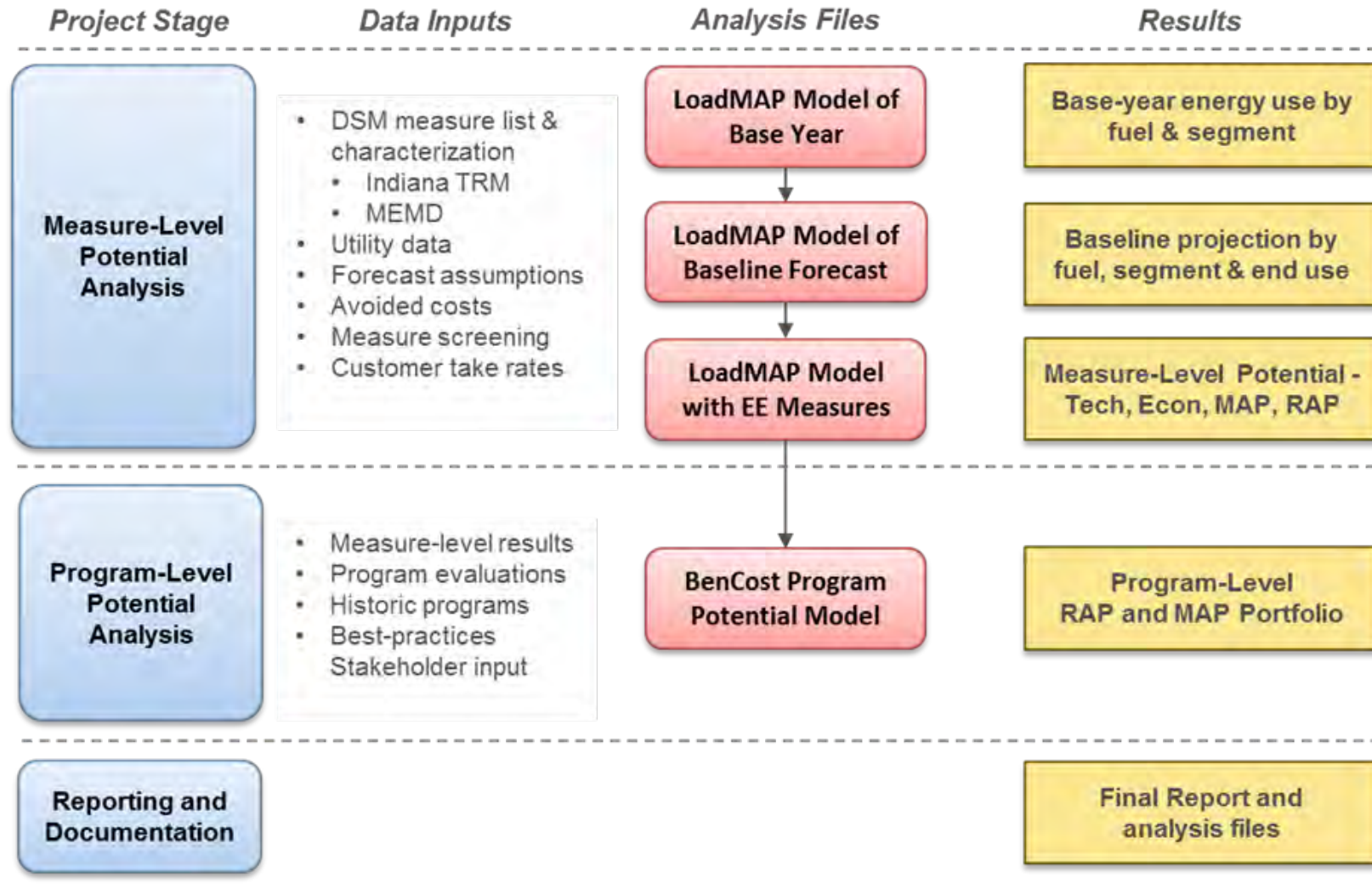
## 2016 Market Potential Study - Highlights

- ❑ In 2016, I&M engaged AEG to complete an EE Market Potential Study with the following objectives:
  - ✓ Develop credible and transparent energy efficiency potential estimates for 2017 through 2036 within the Indiana and Michigan service territory.
  - ✓ Assess potential energy savings (including kW and kWh) associated with each potential area by measure or bundled measure and sector.
  - ✓ Perform the analysis for Indiana and Michigan separately and present the results separately and for both together.
  - ✓ Conduct sensitivity analysis that excludes opt-out customer load within the I&M Indiana Commercial and Industrial sectors.
  - ✓ Provide an executable dynamic model that will support the potential assessment and allow for testing of sensitivity of all model inputs and assumptions.
  - ✓ Develop a final report including summary data tables and graphs reporting incremental and cumulative potential by year from 2017 through 2036.
  - ✓ Develop an energy efficiency portfolio for 2017-2036 based on the potential study results using high, medium, and low spending levels.
  
- ❑ The study identified multiple tiers of energy efficiency potential including technical, economic, maximum achievable and realistic achievable.





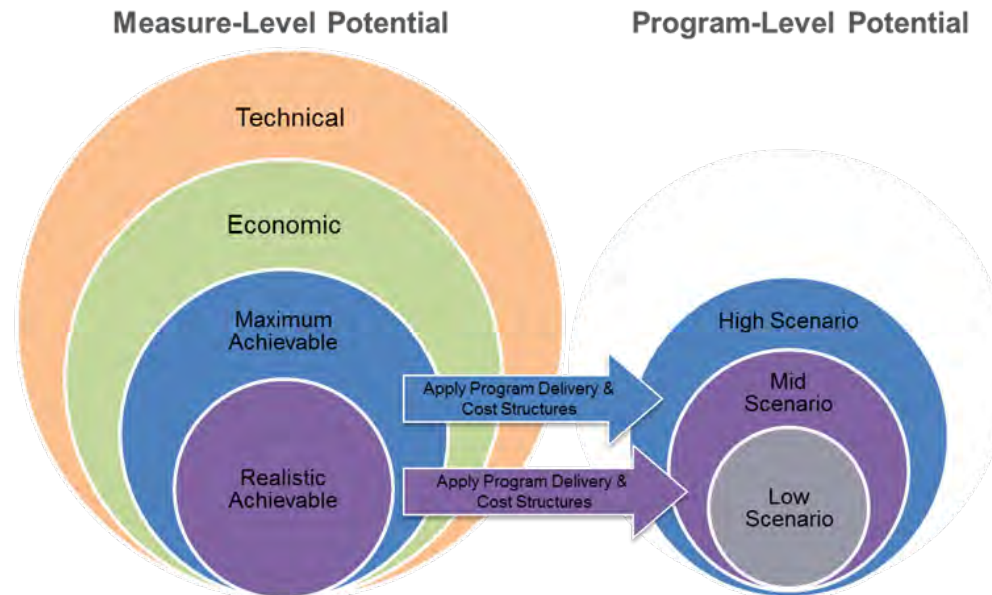
## Analysis Framework





## Energy Efficiency

### Defining Energy Efficiency Potentials & Scenarios



**Technical Potential** - Every customer adopts all feasible measures, regardless of cost or preference

**Economic Potential** - Every customer adopts all cost-effective ( $TRC > 1$ ) measures, does not consider customer acceptance and other factors

**Used in IRP: Maximum Achievable Potential** - Customer adoption of economic measures under ideal market, implementation and preference conditions and an appropriate regulatory framework

**Used in IRP: Realistic Achievable Potential** - Reflects expected program participation given barriers to customer acceptance, non-ideal implementation conditions and limited budgets



## Energy Efficiency

# Summary of MPS Results

	2017	2018	2019	2026	2036
<b>I&amp;M Load Forecast (GWh)</b>	16,587	16,628	16,664	16,974	17,491
<b>Cumulative Savings (GWh)</b>					
Realistic Achievable Potential	140	273	403	1,066	2,122
Maximum Achievable Potential	207	403	592	1,481	2,833
Economic Potential	346	669	966	2,172	3,851
Technical Potential	470	910	1,306	2,950	4,828
<b>Cumulative Savings as a % of Load Forecast</b>					
Realistic Achievable Potential	0.8%	1.6%	2.4%	6.3%	12.1%
Maximum Achievable Potential	1.2%	2.4%	3.6%	8.7%	16.2%
Economic Potential	2.1%	4.0%	5.8%	12.8%	22.0%
Technical Potential	2.8%	5.5%	7.8%	17.4%	27.6%

**The MPS provides the basis for the available DSM in the IRP**





## Energy Efficiency

# IRP EE Resource Development Overview

### ❑ Utilize the Top Measures Identified in MPS & Program Design

- These measures and their potential represents approximately 93% of the total potential from all measures
  - Residential – 97.4%
  - Commercial – 87.0%
  - Industrial – 96.8%

### ❑ IRP will then bundle (group) measures by End-Use to manage the total resources modeled

- These EE Bundles will then be split between Maximum Achievable and Realistic Achievable potential levels
- For the IRP, the Maximum Achievable Bundles will be 75% of the incremental cost and the Realistic Achievable will be 50% of incremental cost
- Managing the total number of Bundles helps the IRP model solve in a reasonable amount of time



## Energy Efficiency

Rank	Residential Measure	2019 Cumulative Energy Savings (MWh)	% of Total
1	Interior Lighting - LED Screw-In Lamps	71,419	42.5%
2	Exterior Lighting - LED Screw-in Lamps	29,857	17.8%
3	Thermostat - WIFI	17,324	10.3%
4	Interior Lighting - Exempted LED Screw-In Lamp <sup>1</sup>	17,242	10.3%
5	Refrigerator - Decommissioning and Recycling	6,201	3.7%
6	Water Heating - Water Heater - ES 2.0 Heat Pump	4,595	2.7%
7	Freezer - Decommissioning and Recycling	3,851	2.3%
8	Windows - High Efficiency	2,065	1.2%
9	Windows - Install Reflective Film	1,509	0.9%
10	Appliances - Air Purifier – ENERGY STAR	1,462	0.9%
11	Water Heater - Temperature Setback	1,061	0.6%
12	Cooling - Central AC – SEER 14	995	0.6%
13	Central AC - Maintenance	988	0.6%
14	Whole-House Fan - Installation	887	0.5%
15	Water Heater - Low-Flow Showerheads	815	0.5%
16	Water Heater - Pipe Insulation	775	0.5%
17	Appliances – Refrigerator – CEE TIER 1	696	0.4%
18	Insulation - Ceiling	693	0.4%
19	Appliances – Dehumidifier – ENERGY STAR	611	0.4%
20	Electronics - Personal Computers	553	0.3%
	<b>Total Top Measures</b>	<b>163,598</b>	<b>97.4%</b>
	<b>Total Cumulative savings in 2019</b>	<b>168,038</b>	<b>100%</b>

Water heater savings increase after 2021 as a result of heat pump water heaters becoming cost-effective from the MPS perspective.



## Energy Efficiency

Rank	Commercial Measure	2019 Realistic Achievable Cumulative Savings (MWh)	% of Total
1	Interior Lighting – LED Screw-in Lamps	38,341	21.7%
2	Interior Lighting - LED High-Bay Fixtures	17,291	9.8%
3	Interior Lighting - Occupancy Sensors	14,131	8.0%
4	Interior Lighting - Linear Lighting	10,192	5.8%
5	Retrocommissioning	9,326	5.3%
6	Exterior Lighting - LED Area Lighting	7,938	4.5%
7	Water Heating - Water Heater EF 2.0 - Heat Pump	6,247	3.5%
8	Cooling - Water-Cooled Chiller - COP 9.77 (0.36 kW/TR)	6,113	3.5%
9	Interior Fluorescent - Delamp and Install Reflectors	4,731	2.7%
10	Exterior Lighting - LED Screw-in Lamps	4,704	2.7%
11	Ventilation - Ventilation	4,586	2.6%
12	Office Equipment - Desktop Computer	4,568	2.6%
13	Chiller - Chilled Water Reset	4,340	2.5%
14	HVAC - Economizer	4,334	2.4%
15	Office Equipment - Server	4,019	2.3%
16	Cooling - Air-Cooled Chiller - COP 4.40 (EER 15.0)	3,907	2.2%
17	Ventilation - Demand Controlled	2,861	1.6%
18	Ventilation - Variable Speed Control	2,330	1.3%
19	RTU - Advanced Controls	2,111	1.2%
20	Refrigeration - High Efficiency Compressor	1,849	1.0%
	<b>Total Top Measures</b>	<b>153,922</b>	<b>87.0%</b>
	<b>Total Cumulative savings in 2019</b>	<b>176,999</b>	<b>100%</b>



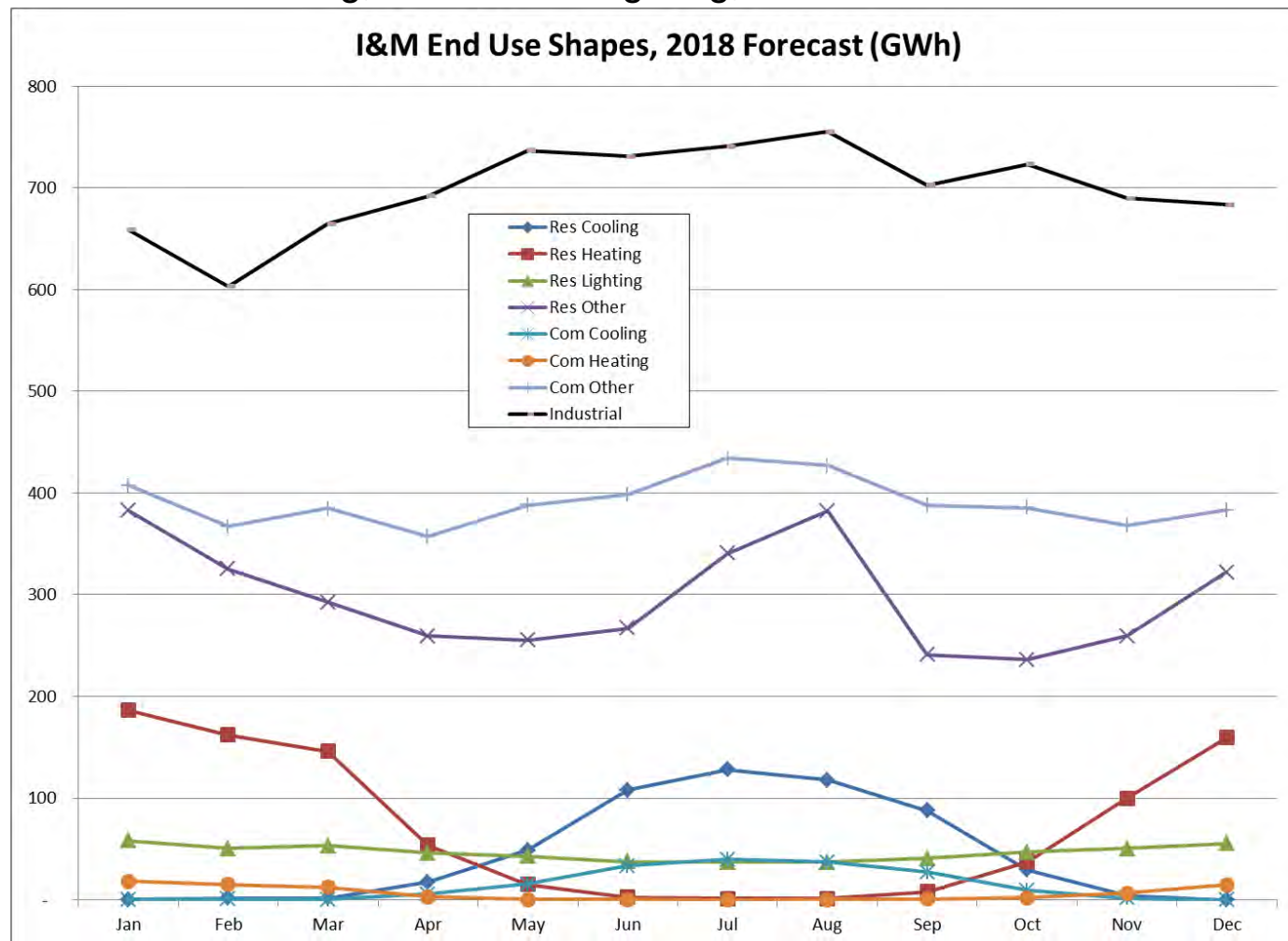
## Energy Efficiency

Rank	Industrial Measure	2019 Realistic Achievable Cumulative Savings (MWh)	% of Total
1	Interior Lighting – LED High-Bay Fixtures Lamps	13,133	22.7%
2	Pumping System - Variable Speed Drive	12,156	21.0%
3	Process - Timers and Controls	4,045	7.0%
4	Pumping System - System Optimization	3,815	6.6%
5	Interior Lighting – LED Screw-in Lamps	3,724	6.4%
6	Compressed Air - Variable Speed Drive	2,987	5.2%
7	HVAC - Economizer	2,249	3.9%
8	Compressed Air - Leak Management Program	1,973	3.4%
9	Exterior Lighting - LED Area Lighting Lamps	1,864	3.2%
10	Fan System - Flow Optimization	1,783	3.1%
11	Cooling - Water-Cooled Chiller - COP 9.77 (0.36 kW/TR)	1,137	2.0%
12	Destratification Fans (HVLS)	1,045	1.8%
13	Insulation - Wall Cavity	1,013	1.8%
14	Interior Lighting – Linear Lighting - T8 - F28 High Eff.	961	1.7%
15	Cooling - Air-Cooled Chiller - COP 4.40 (EER 15.0)	952	1.6%
16	Ventilation - Variable Speed Control	762	1.3%
17	Compressed Air - System Controls	698	1.2%
18	Chiller - Chilled Water Reset	629	1.1%
19	Interior Lighting - Occupancy Sensors	600	1.0%
20	Interior Fluorescent - Delamp and Install Reflectors	431	0.7%
	<b>Total Top Measures</b>	<b>55,956</b>	<b>96.8%</b>
	<b>Total Cumulative savings in 2019</b>	<b>57,809</b>	<b>100%</b>



## Energy Efficiency

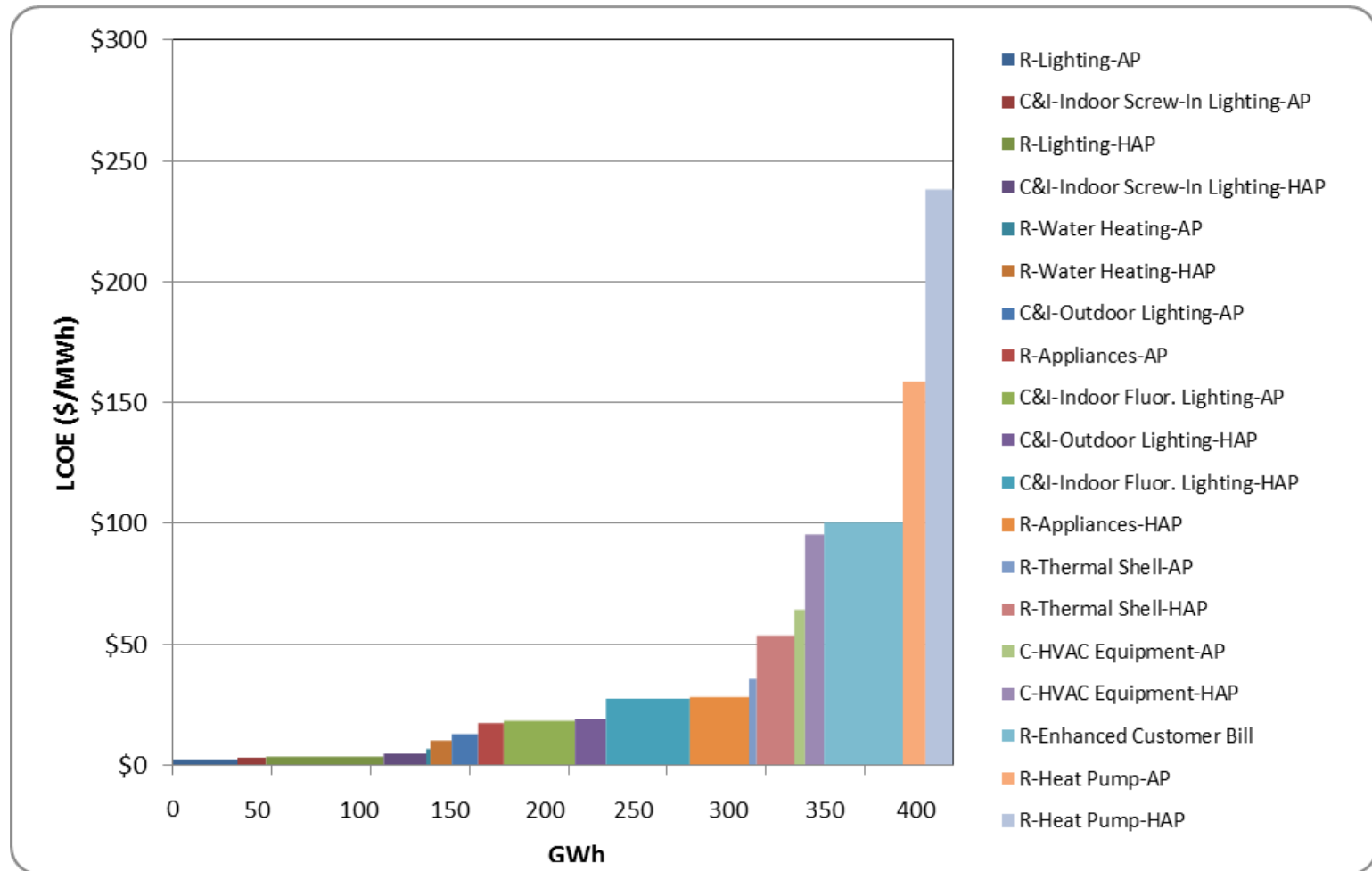
- ❑ I&M's Applicable Load Shapes:
  - Industrial, Commercial Cooling, Commercial Heating, Other Commercial
  - Residential Cooling, Residential Lighting, Other Residential





## Energy Efficiency

### Example of Planned “EE Supply Stack” for IRP Modeling







## Energy Efficiency

### □ Example: Steps to Making a Bundle a Plexos Resource

Bundle	Installed Cost (\$/kWh)	Yearly Potential Savings (MWh) 2019	Yearly Potential Savings (MWh) 2019-2024	Yearly Potential Savings (MWh) 2025-2029	Yearly Potential Savings (MWh) 2030-2040	Bundle Life
Residential Thermal Shell - AP	\$0.24	0	3,926	2,977	4,639	10

#### EXAMPLE: 2025-2029 Energy Reduction (MWh)<sup>(1)</sup> = 1,000

Degradation Profile	Max Units Built In Year	Implementation Cost \$/KWh	Max Capacity MW <sup>(2)</sup>	Implementation Cost \$	Build Cost \$/kW	Firm Capacity MW <sup>(3)</sup>
Year 0 100.00%	2025 3	0.29	0.297	286,822	967	0.1966
Year 1 90.00%	2026 3	0.29	0.297	263,303	888	0.1769
Year 2 73.34%	2027 4	0.30	0.297	218,854	738	0.1441
Year 3 53.79%	2028 6	0.30	0.297	163,725	552	0.1054
Year 4 39.46%	2029 8	0.31	0.297	122,510	413	0.0776

Notes: Yellow Column Headings are Inputs to Plexos

(1) This value should be based on the annual energy reduction of the smallest DSM bundle from all of the DSM alternatives.

(2) Maximum MW reduction from shape file.

(3) Based on coincident peak from shape file.



## Energy Efficiency

### ❑ Demand Response Resources:

- Existing Interruptible Products (Emergency & Economic):
  - Current Contractual Commitments:
    - Industrial - 223 MW
    - Commercial - 61 MW
  - Current & Planned Direct Load Control (Demand-side Management/Load Management) Programs
    - **Residential:** Bring Your Own Thermostat (Indiana and Michigan) Programs Launched in late 2017/early 2018
      - **Forecast Participation:** 13,000 Participants; 18 MW of Demand Savings; 1.75 GWh of Energy Savings; Annual Cost of \$1.65M
    - **Commercial:** End-use Lighting & HVAC load management program
      - **Forecast Participation:** 300; 10 MW of Demand Savings; 3.9 GWh of Energy Savings; Annual Cost of \$1.74M
- Discuss other to be developed DR Programs to model in the IRP





## Energy Efficiency

### □ Volt VAR Optimization Resources:

- I&M has 68 MW of demand reduction potential from VVO; 33 circuits installed, 15 circuits in process; 18 circuits planned in 2019
- IRP Modeled VVO resource, will be updated with New Load Forecast and Cost, below is an illustrative example of VVO resources

Year/ Tranche	Number of Circuits	Capital Investment	Annual O&M	KW Reduction	MWH Reduction	\$VVC / MWH reduced*
Tranche 1	37	\$ 12,358,000	\$ 333,000	6,969	28,694	\$ 83
Tranche 2	34	\$ 11,356,000	\$ 306,000	5,356	22,052	\$ 100
Tranche 3	34	\$ 11,356,000	\$ 306,000	5,268	21,688	\$ 101
Tranche 4	36	\$ 12,024,000	\$ 324,000	5,249	21,609	\$ 108
Tranche 5	37	\$ 12,358,000	\$ 333,000	5,348	22,018	\$ 109
Tranche 6	38	\$ 12,692,000	\$ 342,000	5,303	21,835	\$ 112
Tranche 7	36	\$ 12,024,000	\$ 324,000	4,793	19,734	\$ 118
Tranche 8	38	\$ 12,692,000	\$ 342,000	4,635	19,081	\$ 129
Tranche 9	38	\$ 12,692,000	\$ 342,000	4,391	18,078	\$ 136
Tranche 10	37	\$ 12,358,000	\$ 333,000	4,029	16,586	\$ 144
Tranche 11	35	\$ 11,690,000	\$ 315,000	3,611	14,868	\$ 152
Tranche 12	37	\$ 12,358,000	\$ 333,000	2,889	11,896	\$ 201
Tranche 13	35	\$ 11,690,000	\$ 315,000	2,266	9,330	\$ 242
Tranche 14	25	\$ 8,350,000	\$ 225,000	4,206	17,315	\$ 93

Note: \* \$/MWh is based on the Fixed Charge Rate for a 15 year asset (16.65%) times the Capital Investment, plus the annual O&M expense divided by the MWh reduction.



## Today's Agenda

- ☐ I&M's DSM Performance & Existing Programs
- ☐ DSM Impacts on the Load Forecast
- ☐ Developing DSM Inputs for the IRP
- ☒ **Next Steps for DSM Input Development**
- ☐ Preliminary IRP Assumptions and Portfolios
- ☐ Next Steps



## Next Steps for DSM Input Development

- I&M will consider input from today's meeting and post updated DSM information to its website by May 18, 2018
- Stakeholders submit any additional DSM input by June 1, 2018
- I&M will finalize DSM/EE IRP Inputs and post to IRP website by July 1, 2018



## Today's Agenda

- ☐ I&M's DSM Performance & Existing Programs
- ☐ DSM Impacts on the Load Forecast
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- ☐ Next Steps for DSM Input Development
- ☒ **Preliminary IRP Assumptions and Portfolios**
- ☐ Next Steps



## IRP Inputs and Assumptions

- **Supply Side Resource Costs - Preliminary**
  - Nuclear
  - Coal with 90% Carbon Capture
  - Natural Gas Combined Cycle
  - Natural Gas Simple Cycle
  - Wind
  - Solar
  - Storage
  - Combined Heat and Power



## IRP Inputs and Assumptions

### AEP System-East Zone New Generation Technologies Key Supply-Side Resource Option Assumptions (a)(b)(c)

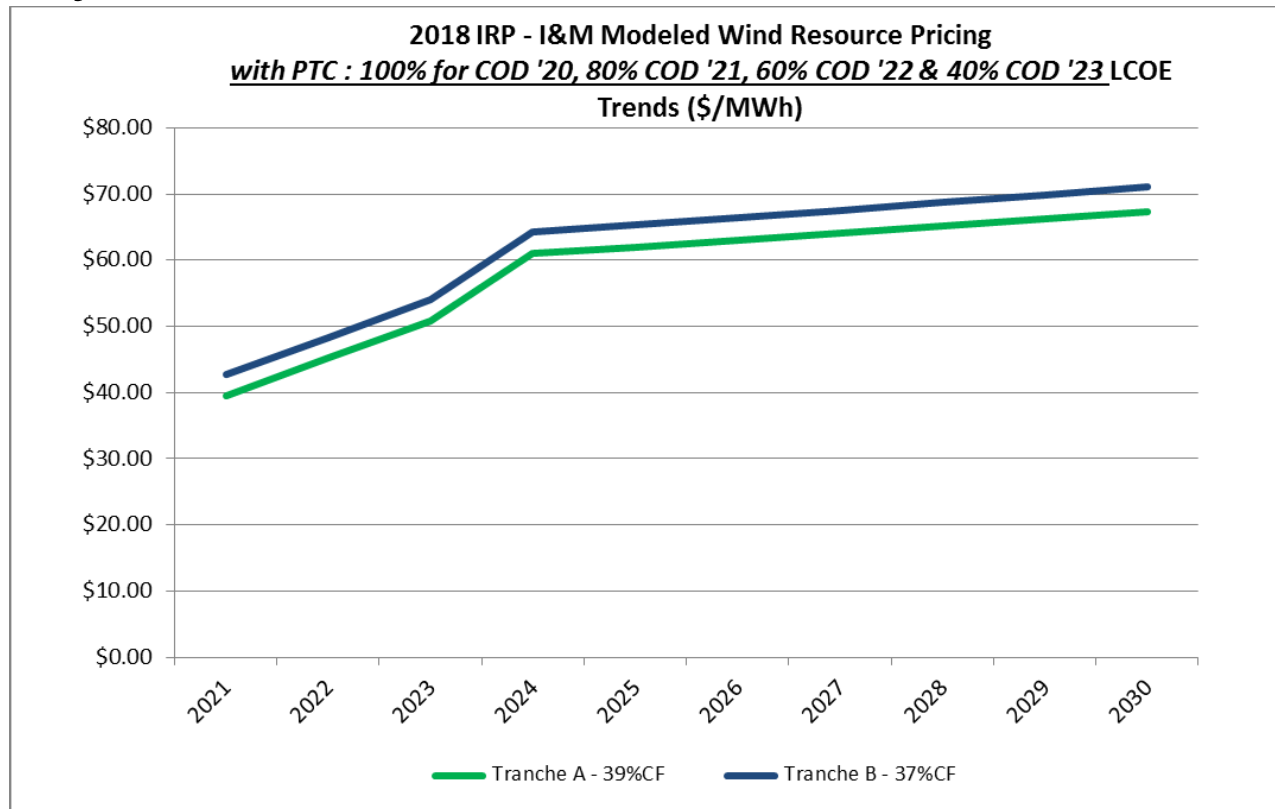
Type	Capacity (MW) (g)			Installed Cost (c,d) (\$/kW)	Full Load Heat Rate (HHV,Btu/kWh)	Fuel Cost (f) (\$/MBtu)	Variable O&M (\$/MWh)	Fixed O&M (\$/kW-yr)	SO2 (Lb/mmBtu)	Emission Rates		Capacity Factor (%)	Overall Availability (%)	LCOE (k) (\$/MWh)	
	Std. ISO	Winter	Summer							NOx (Lb/mmBtu)	CO2 (Lb/mmBtu)				
Base Load															
Nuclear	1,610	1,690	1,560	7,400	10,500	1.2	6.2	143.5	0.0000	0.000	0.0	90	94	171.7	
Base Load (90% CO2 Capture New Unit)															
Pulv. Coal (Ultra-Supercritical) (PRB)	540	570	520	8,900	12,500	4.4	5.6	95.8	0.0650	0.050	21.3	85	90	244.0	
Base / Intermediate															
Combined Cycle (1X1 "J" Class)	540	570	700	1,200	6,300	7.2	2.0	7.3	0.0007	0.007	117.1	60	89	87.2	
Combined Cycle (2X1 "J" Class)	1,083	1,140	1,410	900	6,300	7.2	1.7	4.8	0.0007	0.007	117.1	60	89	78.7	
Combined Cycle (2X1 "H" Class)	1,150	1,210	1,500	900	6,300	7.2	1.6	4.3	0.0007	0.007	117.1	60	89	75.9	
Peaking															
Combustion Turbine (2 - "E" Class) (h)	182	190	190	1,200	11,700	7.2	3.9	9.4	0.0007	0.008	117.1	25	93	177.3	
Combustion Turbine (2 - "F" Class, w/evap coolers) (h)	486	510	500	700	10,000	7.2	6.1	5.0	0.0007	0.008	117.1	25	93	139.3	
Aero-Derivative (2 - Small Machines) (h,i)	120	120	130	1,400	9,700	7.2	2.4	36.9	0.0007	0.008	117.1	25	97	175.4	
Recip Engines (12 - w/SCR, Natural Gas Only)	220	240	220	1,200	8,300	7.2	5.4	6.0	0.0007	0.008	117.1	25	98	148.0	
Storage Battery (4 Hour-Lithium Ion)	10	10	10	2,200	87% (j)	--	--	142.3	--	--	--	25	99	275.0	

Notes: (a) Installed cost, capability and heat rate numbers have been rounded  
(b) All costs in 2018 dollars. Assume 2.17% escalation rate for 2018 and beyond  
(c) \$/kW costs are based on nominal capability  
(d) Total Plant Investment Cost w/AFUDC (AEP-East rate of 5.5%, site rating \$/kW)  
(f) Levelized Fuel Cost (40-Yr. Period 2018-2057)  
(g) All Capabilities are at 1,000 feet above sea level  
(h) Includes Dual Fuel capability and SCR environmental installation  
(i) Includes Black Start capability  
(j) Denotes efficiency, (w/ power electronics)  
(k) Levelized cost of energy based on assumed capacity factors shown in table



## IRP Inputs and Assumptions

# Preliminary Wind Resources for the IRP

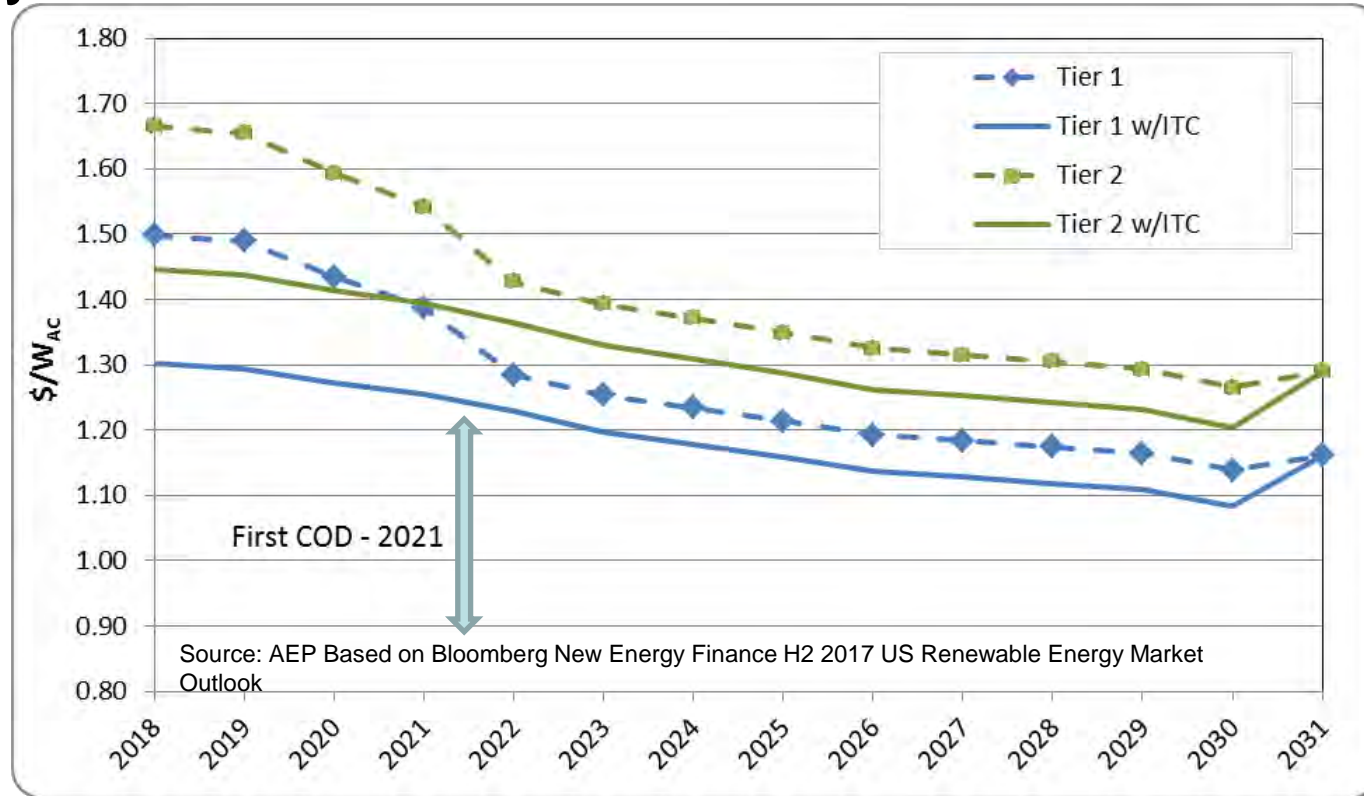


- Installed Cost based on Bloomberg New Energy Finance's H2 2017 Renewable Energy Market Outlook
- Two Tranches Available as a Modeling Constraint – Tranche A & Tranche B both reflect impact of the Production Tax Credit
- 300MW of Wind Available per year; 150MW for each Tranche
- Expected Capacity Factor: 39% for Tranche A & 37% for Tranche B



## IRP Inputs and Assumptions

### Preliminary Solar Resources for the IRP



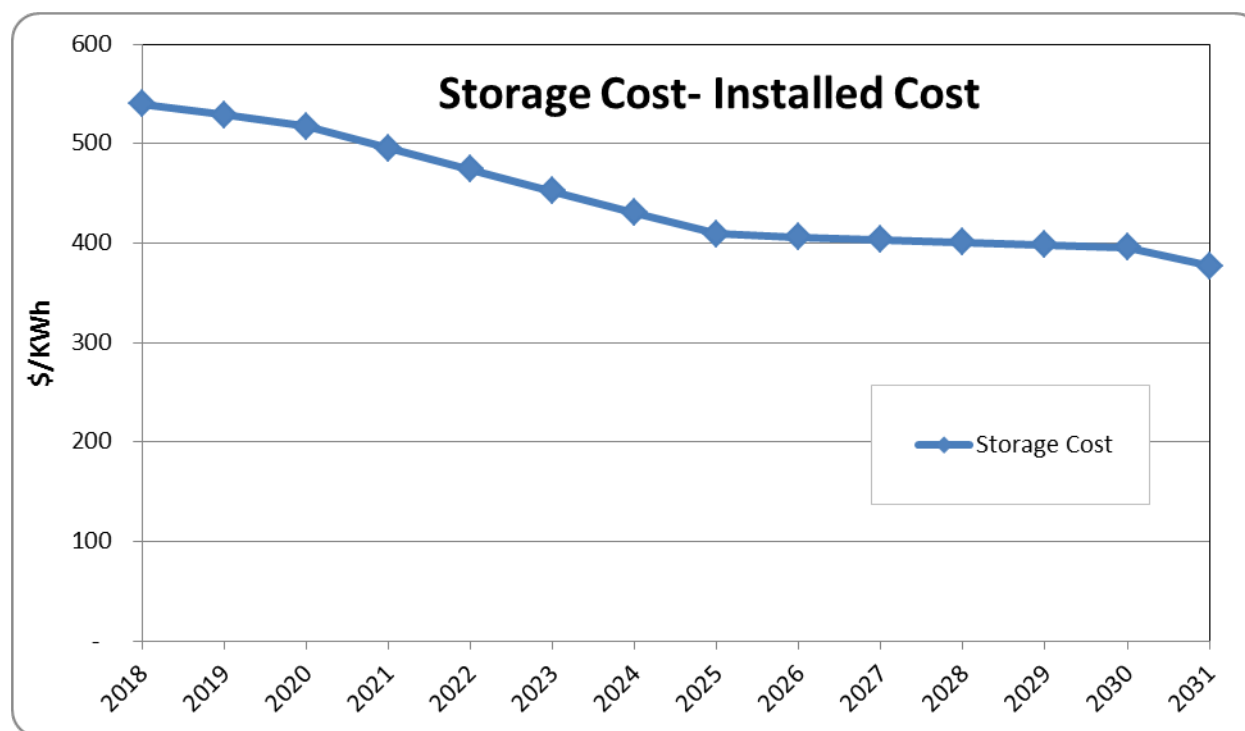
- Two Tranches Available as a Modeling Constraint – Tier 1 and Tier 2 Pricing with Normalized Investment Tax Credit impact
- 300MW of Solar Available per year; 150MW at Tier 1 & 150MW at Tier 2
- Expected Capacity Factor ~24.4%, from Single Axis Tracking system
- For a 2021 Commercial Operation Date ~LCOE \$60 to \$70/MWh





## IRP Inputs and Assumptions

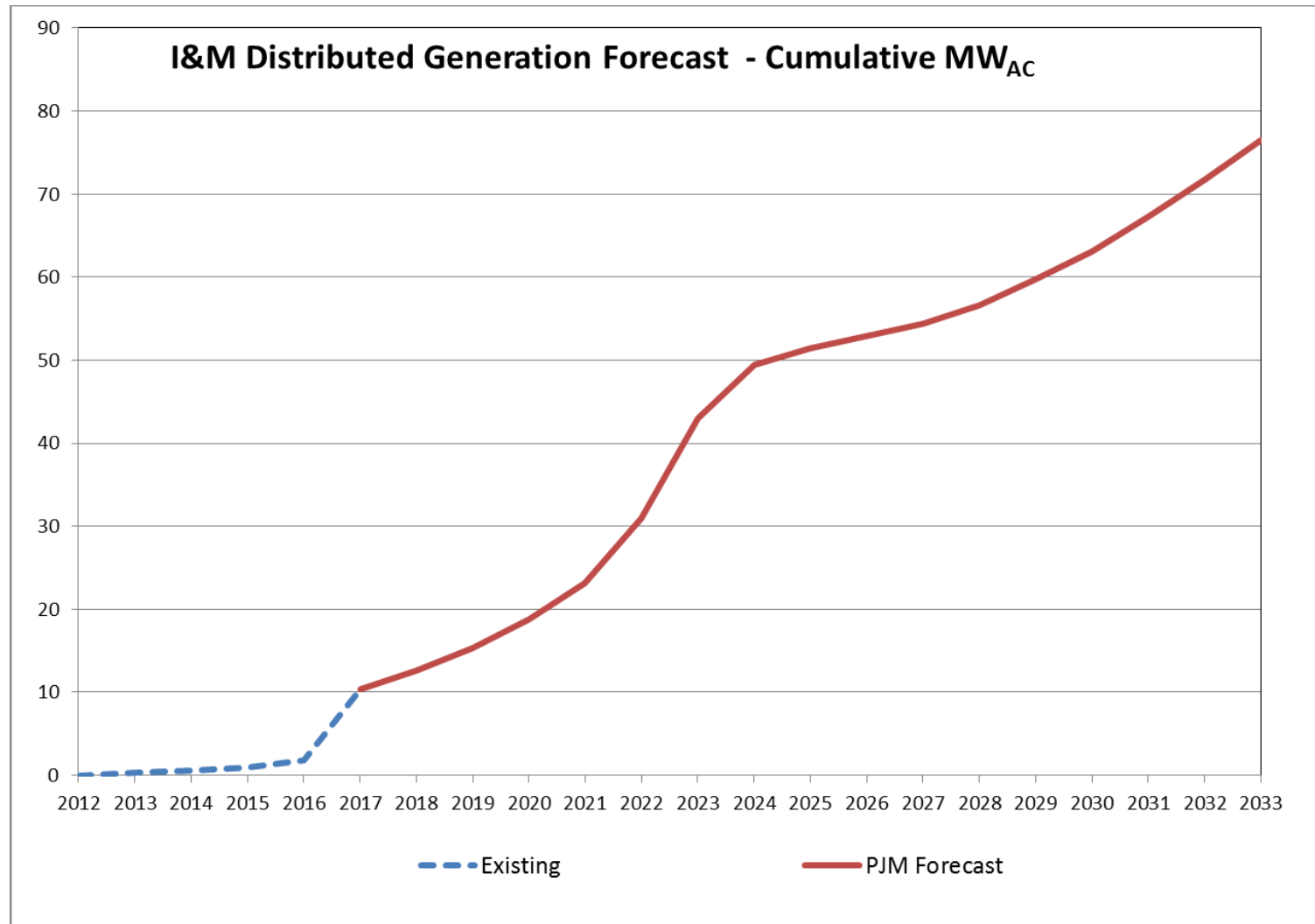
### Preliminary Energy Storage – 10MW/40MWh Resource



- Based on Lithium Ion technology, Energy Product
- Cost Estimates based on Internal Estimates and information from EPRI and Storage Suppliers



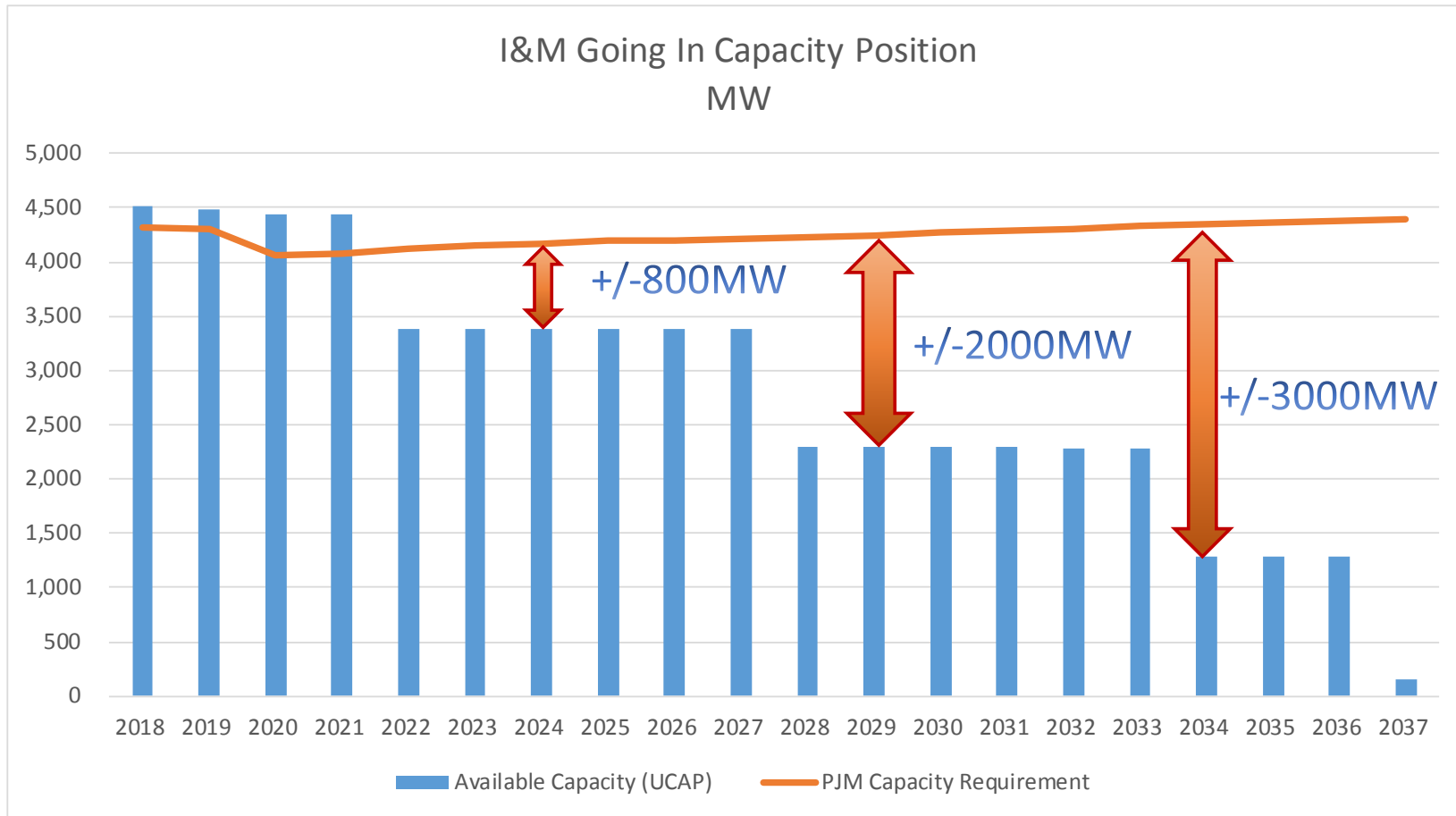
## IRP Inputs and Assumptions



Forecast is based on PJM's November 5, 2017 Distributed Solar Forecast



## Portfolio Assumptions – I&M Going In Capacity Position

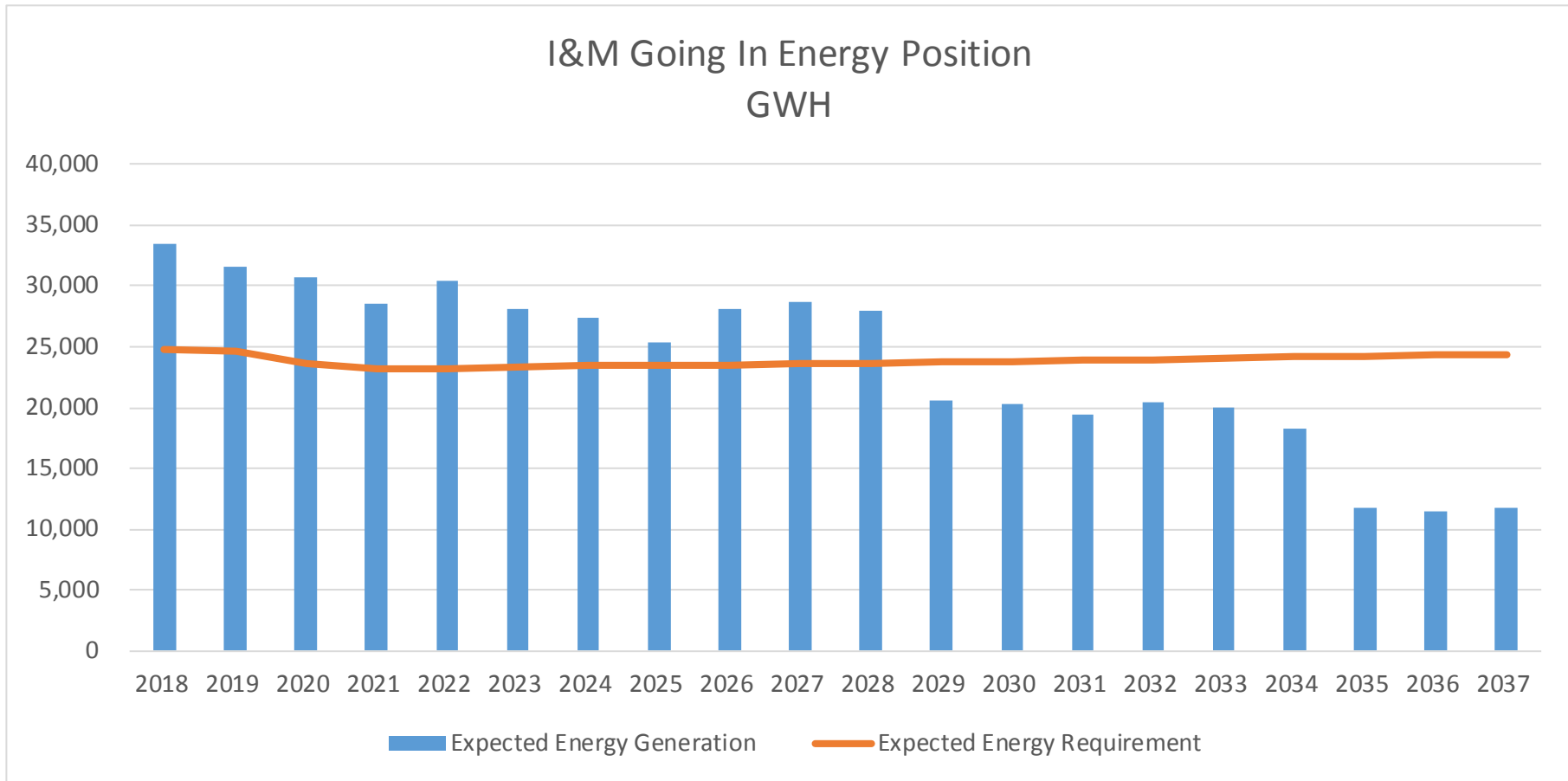


Capacity position based on excluding from the portfolio:

- RP2 (2022), RP1 (2028)
- DCCNP1(2034), and DCCNP2 (2037)
- No new resource additions



## Portfolio Assumptions – I&M Going In Energy Position



Energy position based on excluding from the portfolio:

- RP2 (2022), RP1 (2028)
- DCCNP1(2034), and DCCNP2 (2037)
- No new resource additions



## Preliminary IRP Portfolios

Various portfolio options that may be analyzed, all portfolios assume:

Rockport 2 lease expires in 2022 and is not renewed\*, Rockport 1 is retired prior to adding FGD in 2028\*, Cook Units 1 & 2 are retired in 2034 & 2037, respectively:

### 1. Conventional Portfolio

- Meet energy demand through economically selected resources including universal solar, wind, storage and DSM/EE programs
- Add peaking capacity (CT or capacity purchase) in 2022, NGCC in 2028, 2034, & 2037

### 2. 12 - Year Peaking Plan

- Meet energy demand through economically selected resources including universal solar, wind, storage and DSM/EE programs
- Add peaking capacity (CT or capacity purchase) in 2022 & 2028, NGCC in 2034 & 2037

### 3. 15 - Year Peaking Plan

- Meet energy demand through economically selected resources including universal solar, wind, storage and DSM/EE programs
- Add peaking capacity (CT or capacity purchase) in 2022 & 2028, & 2034, NGCC in 2037

### 4. Stakeholder Defined

- Meet energy demand through economically selected resources including universal solar, wind, storage and DSM/EE programs
- ??? You Decide

\*RP1 FGD addition and the extension of RP2 current lease terms will be evaluated relative to alternative resources.



## Status and Timing of Stakeholder Input

- By June 1, 2018, stakeholders are asked to provide comments on:
  - The portfolio components (resources) that should be considered
  - The attributes of resources (cost and performance) to be considered
  - Considerations for economic scenarios
  - Considerations for evaluating risk
- I&M plans to begin evaluating scenarios and modeling in early July



## Next Steps

- I&M will consider input from today's meeting and post updated DSM information to its website by May 18, 2018
- Stakeholders submit any additional DSM/EE input by June 1, 2018
  - I&M plans to finalize DSM/EE IRP inputs by July 1, 2018
- Stakeholders provide additional input on I&M's cost assumptions and resource portfolios by June 1, 2018
  - I&M's plans to begin evaluating scenarios and modeling in early July
- I&M plans to publish final IRP inputs (e.g. Load Forecast, Fundamental Commodity Forecast, Supply-side Resource Key Characteristics, etc) and modeling scenarios by early to mid-July
- I&M will present preliminary modeling results at the August 1, 2018 stakeholder meeting





## Follow-up Steps in the Stakeholder Process

Meeting	Date	Topic
1	February 15, 2018 Northeast Indiana Innovation Center 3211 Stellhorn Road Fort Wayne, IN 46815	2018 IRP Kick-off Meeting - Stakeholder Process & Scenario Discussion
2	April 11, 2018 Barnes & Thornburg 11 S. Meridian St. Indianapolis, IN 46204	Considerations for Modeling DSM in the 2018 IRP & Update on the IRP
3	August 1, 2018 I&M South Bend Service Center 2929 Lathrop St. South Bend, IN 46628	Final Inputs, Portfolios, Scenarios & Initial Modeling Results
4	Sept. - Oct. 2018	Modeling Results & Preferred Portfolio Discussion

In addition to the four stakeholder workshops, teleconference discussions may be held as needed





Thank You for Your Participation  
and Safe Travels

See You August 1<sup>st</sup>, at  
9:30 for our  
3<sup>rd</sup> Stakeholder Meeting

## > Itron white paper

### Incorporating DSM into the Load Forecast

*Stuart McMenamin / Mark Quan  
Itron Energy Forecasting & Load  
Research*





Introduction	3
Energy Forecasting Methods	3
DSM Forecasting Issue	4
DSM Impact Accounting	4
Model Approaches	7
Conclusions	15
Glossary	17

## Incorporating DSM into the Load Forecast

### Introduction

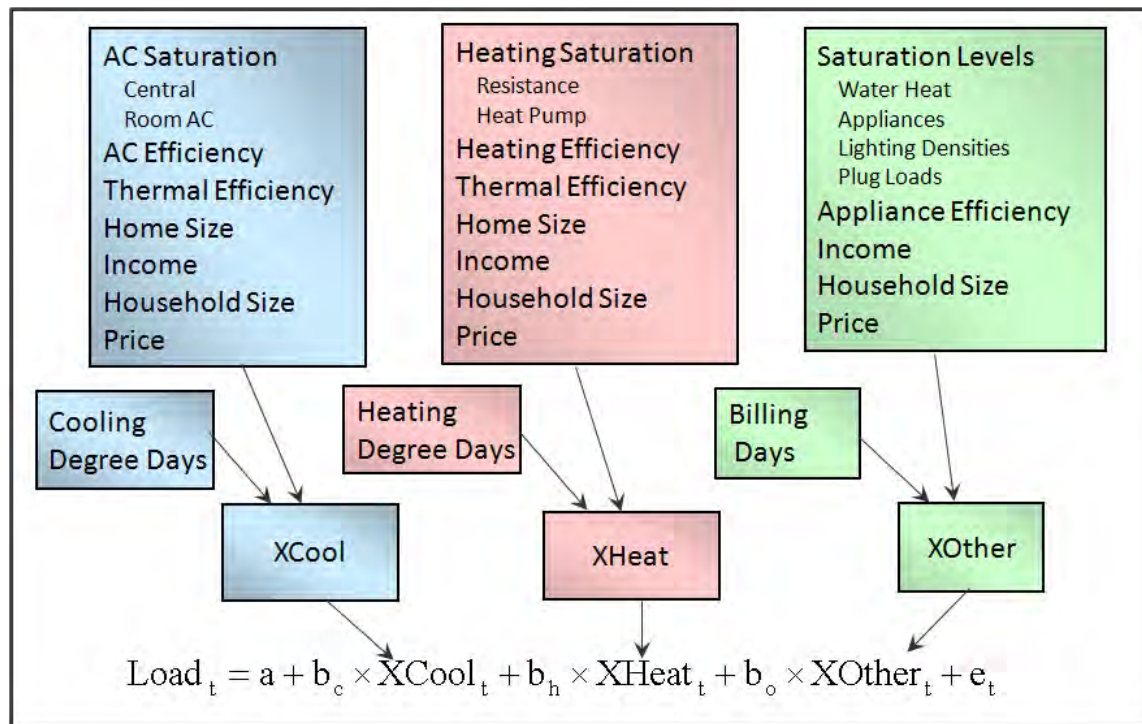
Since 1970, Demand Side Management (DSM) programs have been used to reduce energy demand growth. These programs include measures to increase conservation levels, improve energy efficiency, and deploy load management techniques. With today's focus on environmental issues and energy independence, companies and policy makers are renewing their interest in DSM programs. Recently, several utilities and government agencies have set accelerated DSM targets for future years.

The purpose of this paper is to discuss methods for adjusting load forecasts to account for DSM programs. This paper begins with an overview of current industry forecasting practices and highlights key DSM accounting issues. This is followed by a discussion of methods that can be applied to the econometric modeling frameworks used throughout the electric industry.

### Energy Forecasting Methods

Each year, utilities forecast sales for budget and planning purposes. The process typically includes forecasting monthly sales by rate class using an economic model driven by weather and economic variables. More recently, many utilities have adopted Itron's Statistically Adjusted End-Use (SAE) modeling approach to include greater end-use information into the forecast process. This approach is depicted in Figure 1.

Figure 1: General Depiction of SAE Method



The SAE approach begins with regional estimates of end-use saturation levels, average efficiency levels, thermal efficiency levels, and end-use energy estimates in a reference year. These estimates are developed from analysis provided by the U.S. Energy Information Administration (EIA). For each end-use, these data represent the average efficiency of the appliance stock in place in each year. The average efficiency forecasts are based on technology level analysis about the range of efficiency levels available in the market, assumptions about how this range is expected to evolve in the forecast period, and assumptions about how efficiency standards will limit the range. The



analysis proceeds with stock accounting to bring the new equipment into the mix of existing equipment, resulting in a forecasted time-path for average efficiency values.

Although EIA efficiency data are typically used, regional data are often adjusted or replaced to agree with utility data from local saturation surveys. In addition, energy consumption levels by end-use are adjusted to agree with use-per-customer data and aggregate weather sensitivity of the local utility. These data are then used to construct aggregate end-use variables, XCool, XHeat, and XOther.

The general equation for the SAE model is shown at the bottom of Figure 1. In this equation, XHeat, XCool and XOther are structured variables that account for saturation levels, average efficiency levels, and usage trends of end-use categories in an econometric framework. Once these X variables are computed, the econometric equation calibrates the end-use inputs to the historical sales data for the utility and the monthly sales forecast is created.

## DSM Forecasting Issue

When applying the SAE framework, DSM activity is naturally incorporated in the efficiency assumptions and the calibration to historic sales data. Efficiency assumptions incorporate national level DSM impacts. Calibration incorporates specific utility DSM impacts.

In the underlying analysis for the efficiency assumptions, model parameters and hurdle rates used in technology choice modeling are calibrated based on efficiency levels implied by new appliance shipment data. To the extent that these observed market outcomes reflect DSM activity at the national level, the efficiency forecasts embed the historical levels of DSM. For example, when DSM programs reflect the purchase of above-standard options, the model parameters are calibrated to these market outcomes. As a result, there is an implicit assumption that future outcomes will continue to be influenced by continued program activity promoting purchase of options that are better than standards.

In the final calibration of the SAE variables to historic sales data, model coefficients are fit to historic data that may have been impacted by utility specific DSM programs. To the extent that a utility has implemented DSM programs in the past, these programs' savings would be embedded into the sales history by lowering sales. Any economic projection of the sales history will contain the implicit assumption that comparable programs will be operated in the future.

Because DSM impacts are embedded in the SAE framework, we must consider how to modify the SAE framework to account for historic and future DSM. This discussion begins with an overview of DSM impact accounting and the data required by the forecaster.

## DSM Impact Accounting

The business case for future DSM programs is typically developed through a market assessment. The assessment provides estimates of market potential for energy savings at the technology level. The assessments are ultimately translated into programs to promote efficient technologies. Program planning includes assumptions about technology impacts, measure life, and adoption levels. Finally, the assumptions are translated into a stream of costs and benefits in the form of energy savings and the value of these savings.

Once a program is implemented, participation levels are monitored, and initial impacts are estimated based on these levels. The success of the implemented program is measured through program evaluations. Topics in an evaluation study include program processes, participation levels, free rider rates, and estimation of the actual energy impacts achieved for program participants.

The primary need for the load forecaster is a year-to-year or month-to-month series that can be used in the SAE modeling framework. Both the initial program assessments and the completed program evaluation studies are useful for developing the data series required by the forecaster in order to incorporate DSM into the load forecast.

## Incorporating DSM into the Load Forecast

### Program Impact Streams

Each year as programs are implemented, the impacts are estimated based on participation levels. This is depicted in Figure 2 which shows the time stream of impacts (energy savings) from three years of program activity. Year A programs, shown in blue, have partial impacts in the first year (Year 1) and full impacts in subsequent years (Year 2 to Year 6). Based on measure life assumptions, the impacts ramp down in Year 7 and Year 8. There are no impacts for the Year A programs in Year 9 and 10. Year B programs, shown in red, have partial impacts in the initial year (Year 2), followed by a similar stream of impacts to the right (Years 3 to 9). Year C programs, shown in orange, finish the picture, with initial impacts beginning in Year 3.

### Cumulative Program Impacts

The forecaster has no direct interest in the accomplishments of individual programs or the first-year impact of programs. The relevant question involves how much energy sales are reduced in each year from the combination of all programs run from a point in time. For the discussion of modeling methods, this is the **cumulative impact**. As shown in Figure 2, the cumulative impact of programs in any year is the vertical sum across program years of the continuing impacts of these programs. For example, in Year 3, the cumulative impact of Programs A, B, and C is represented by the blocks labeled  $A3 + B2 + C1$ .

Note, that the term “cumulative” is also used in some cases to represent the stream of impacts from programs in a given year (e.g.,  $A1 + A2 + \dots + A7$ ). This is the stream that would be discounted to a present value to calculate benefit/cost ratios. In the forecasting discussion, this paper will attempt always to use the term cumulative to mean the vertical sum of the impacts in a year, not the horizontal sum of an impact stream over time.

**Figure 2: Illustration of Impact Accounting and Aggregate Impacts**

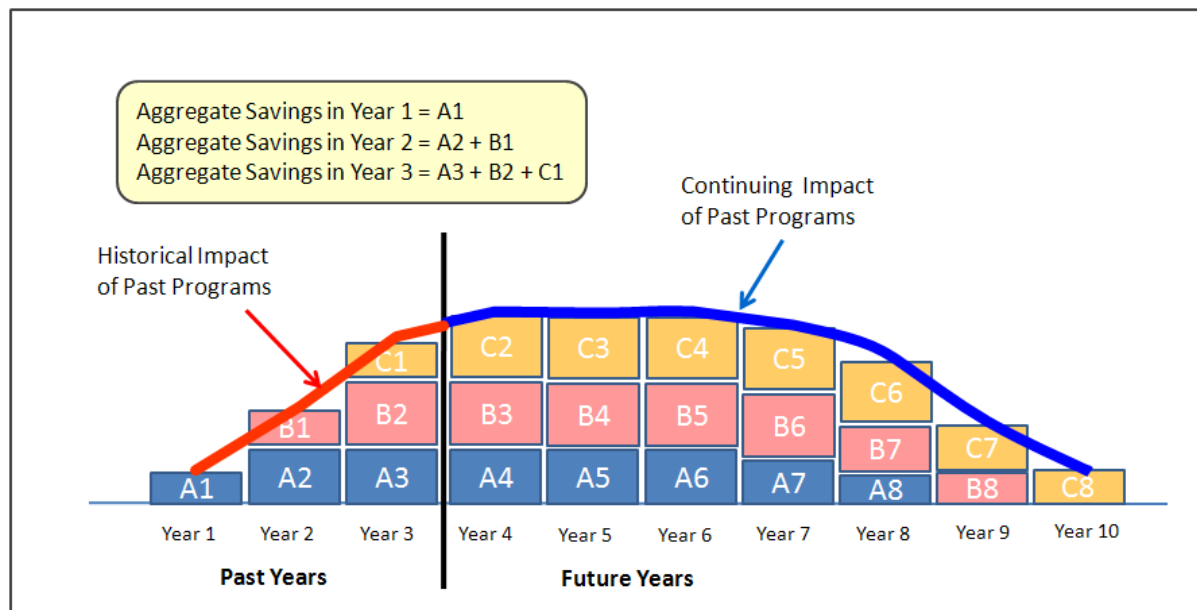
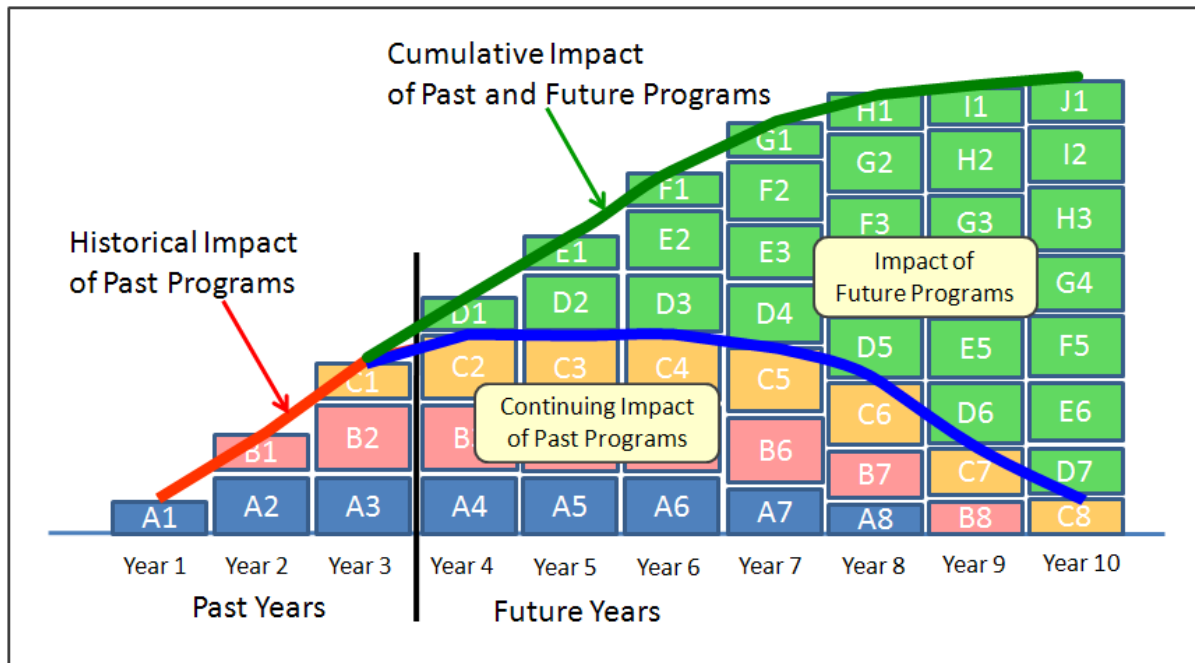


Figure 2 illustrates the key timing issues associated with DSM impact accounting. In the example, programs are run in each of the three historical years. The total energy impact from the historical program activity is represented by the red line. If there are no further programs in years 4 and beyond, then the blue line represents the continuing cumulative impact of past programs. The decline in the blue line shown in Figure 2 is attributed to the end of the measure life.



Figure 3 provides an extension to include estimates of the expected impacts of future as well as past programs. Future programs are shown as green boxes and are labeled based on the program year (D to J). The cumulative impacts of past and future programs are represented by the solid green line at the top of the impact stack for each year. Because the new program impacts are relatively stable each year, the green line eventually bends over as the decay in impacts from program years A, B, and C offsets some of the gains from the future program efforts.

**Figure 3: Illustration of Impact Accounting with Future Programs**



### Issues for Calculation of Program Impacts

The program impact data needed by the forecaster should represent both the historical impact of past programs and the cumulative impact of past and future programs. Generally, historical savings estimates are derived from program evaluations and future program estimates are obtained from program assessments. In both cases, underlying assumptions may vary and conflict with forecast assumptions. The key issues that should be addressed when developing the impact streams are as follows.

- Weather:** Many DSM programs seek to reduce energy consumption related to heating and cooling impacts. In program assessments, impacts are often estimated under the assumption of normal weather conditions. Program evaluations generally reflect patterns based on actual weather conditions. To be consistent with the statistical modeling process used in forecasting, the historical impact of past programs estimates needs to reflect the weather pattern that actually occurred and future impacts should reflect the same weather patterns used in the load forecasting process. This consistency will ensure that DSM savings associated with heating and cooling are consistent with the weather pattern that will be used in the load forecast.
- Realization Rates:** During the program assessment, initial estimates of DSM savings are made based on assumptions about technology adoption levels and the associated energy impacts. After the program is implemented, evaluation studies will show that actual savings will differ from the planning estimates based on the actual participation levels, estimated free rider rates, and the estimated energy usage impacts. The difference between the planning estimates and final evaluation results of program impacts reflect the

## Incorporating DSM into the Load Forecast

estimated realization rates. Both the historical impact of past programs and the cumulative impact of past and future programs should be consistent and reflect the realized savings from DSM programs.

- **Reference Efficiency Levels:** DSM program savings are generally calculated relative to the naturally occurring efficiency level, which reflects both energy efficiency standards and adoption of above-standard technologies based on market forces. Over time, the reference efficiency level will change because of changes in efficiency standards and changes in market conditions. These changes are reflected in the SAE efficiency trends. To be consistent with the underlying modeling process, both the historical impact of past programs and the cumulative impact of past and future programs should be measured relative to these dynamic reference levels (efficiency levels that would have occurred in absence of the programs).
- **Technology Life Cycle:** DSM programs often include the installation of technologies that persists for multiple years. Equipment related measures have lives related to the equipment life cycle. Some measures have very long lives, such as increased insulation levels in new construction. Other measures and devices may have relatively short lives, such as efficient general service lamps, and these may be affected by measure retention rates as well as measure life times. During the historical and forecast period, both the historical impact of past programs and the cumulative impact of past and future programs should reflect the lifecycle and retention rates for the corresponding technologies. In the forecast period, the direct savings expected from past programs should decay with time based on these factors when not accounting for market transformation credits.
- **Market Transformation:** DSM analysis sometimes calculates benefits for a program that exceed the underlying technology lifecycle. The analysis assumes that the program transforms the market or participant behavior, leading to subsequent adoption or replacement outside of the program. In Figure 2, no recognition of market transformation has been included. If DSM impacts include significant market transformation effects, extra care must be taken to insure that this does not lead to double counting of trend effects already included in SAE models.

Regardless of the modeling method that is used, it is important that DSM accounting be performed on a regular and consistent basis. The goal is to create for each program year the stream of expected impacts relative to what would have happened without the program.

## Model Approaches

Once the historic DSM series has been developed, three potential econometric frameworks may be applied to account for DSM in the forecast period. The methods are designed to adjust the load forecast by accounting for the amount and the continuing momentum of the historic DSM contained in the load forecast model.

### Method 1: Add Back

In this method, historic loads are reconstituted by adding into the load history the historical impact of past programs<sup>1</sup>. The reconstituted loads are shown in equation (1). These loads represent what energy consumption would have been had there never been any utility specific DSM programs. The reconstituted loads are used as the left-hand variable to estimate the “NoDSM” forecast model (equation 2) and generate the forecast in absence of DSM (equation 3). The final forecast of energy use is given by the “NoDSM” model forecast reduced by the forecasted cumulative impact of past and future programs (equation 4).

---

<sup>1</sup> For the historical reconstitution of loads, the historical impacts of past programs are used from Figure 2. In the forecast period, the forecast (equation 4) is adjusted by the historical and continuing impacts of past programs shown in Figure 3. All values are cumulative.





$$\text{Load}_t^{\text{NoDsm}} = \text{Load}_t^{\text{Measured}} + \text{DSM}_t^{\text{PastPgms}} \quad (1)$$

$$\text{Load}_t^{\text{NoDsm}} = F(\text{Econ}_t, \text{Wthr}_t, \dots) + e_t \quad (2)$$

$$\text{Fcst}_t^{\text{NoDsm}} = F(\text{Econ}_t^{\text{Fcst}}, \text{Wthr}_t^{\text{Norm}}, \dots) \quad (3)$$

$$\text{Fcst}_t = \text{Fcst}_t^{\text{NoDSM}} - \text{DSM}_t^{\text{PastPgms}} - \text{DSM}_t^{\text{FuturePgms}} \quad (4)$$

where

$F(\dots)$	= Forecasting model (e.g. regression model) with residual values (e)
$\text{Econ}$	= Economic historical data
$\text{Econ}^{\text{Fcst}}$	= Economic variable forecast
$\text{Wthr}$	= Actual historical weather data
$\text{Wthr}^{\text{Norm}}$	= Normal weather scenario
$\text{DSM}^{\text{PastPgms}}$	= Cumulative historical and continuing impact of past programs <sup>1</sup>
$\text{DSM}^{\text{FuturePgms}}$	= Cumulative impact of future programs <sup>2</sup>

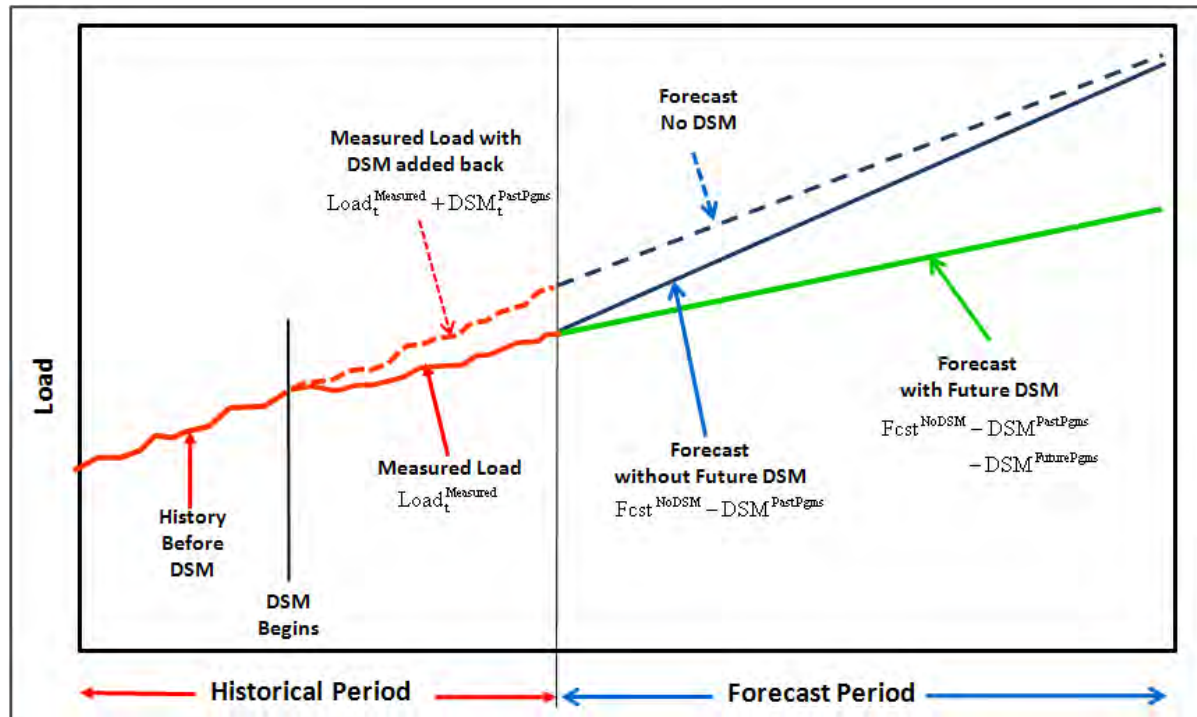
The estimate of DSM impacts from past programs ( $\text{DSM}^{\text{PastPgms}}$ ) in the forecast period represents the continuing impact of past programs and reflects the measure life of actions caused by these programs over forecast horizon. These impacts are shown as the blue line in Figures 2 and 3. The forecast of the impacts of future programs ( $\text{DSM}^{\text{FuturePgms}}$ ) is the expected savings from new programs or renewal of existing programs in the forecast horizon. These impacts are shown as the green boxes in Figure 3. The combination of the two impacts (past and future) is represented by the green line in Figure 3.

Figure 4 illustrates the forecast method. In this figure, the solid red line illustrates historical measured loads ( $\text{Load}^{\text{Measured}}$ ). The dashed red line represents the reconstituted loads with historical DSM impacts added ( $\text{Load}^{\text{Measured}} + \text{DSM}^{\text{PastPgms}}$ ). The model is developed using the reconstituted loads as the left-hand variable (equation 2). This equation represents an estimate of what would have happened without DSM programs. The model generates the forecast of reconstituted load ( $\text{Fcst}^{\text{NoDSM}}$ ) and is shown by the dashed blue line (equation 3). The dashed blue line is then adjusted downward to account for the continuing impacts of past DSM program ( $\text{DSM}^{\text{PastPgms}}$ ) and the impacts of future DSM programs ( $\text{DSM}^{\text{FuturePgms}}$ ). The final forecast is shown as the green line (equation 4).

<sup>2</sup> The forecast (equation 4) is reduced by the cumulative impacts of future programs shown in Figure 3 by the green boxes.

## Incorporating DSM into the Load Forecast

Figure 4: Method 1 Illustration



### Key Issues

The strength of this method is that it explicitly accounts for historical and forecasted DSM at the utility level. However, this strength exposes the primary issue, which is the reliance on accurate and consistent estimates of cumulative program impacts in the past and every year in the future.

- DSM Data Accuracy.** Because the historic DSM savings estimates are used to reconstitute load, the accuracy of these estimates has a significant impact on the econometric model parameters and forecast. It is important that the estimated program impacts are conceptually correct and contain consistent assumptions around the natural efficiency gains contained in the econometric model.
- National DSM Assumption.** In the SAE model framework, the reconstitution of loads does not make any adjustments for the national level DSM that is included in the energy efficiency trends. As such, the SAE framework still assumes that national energy efficiency trends continue at a steady pace. To estimate the NoDSM model ( $Fcst^{NoDSM}$ ) without national level DSM, it would be necessary to estimate what efficiency trend values would have been throughout history without any DSM programs and to forecast what they would be without further programs. This is an awkward task because the default (EIA) data include DSM program impacts and there are no readily available estimates without these impacts.



## Method 2: DSM Variable

In this method, an exogenous DSM variable is included as a right-hand variable in the SAE model. The generalized equation is shown in (5). In this equation, the DSM variable represents the cumulative historical impact of past programs.<sup>3</sup> Also, on the right-hand side are the SAE variables.

$$\text{Load}_t^{\text{Measured}} = F(\text{DSM}_t^{\text{PastPgms}}, \text{XHeat}_t, \text{XCool}_t, \text{XOther}_t) + e_t \quad (5)$$

where

$F(\dots)$	=	Forecasting model (e.g. regression model) with residual values (e)
$\text{XHeat}_t$	=	SAE Heating variable
$\text{XCool}_t$	=	SAE Cooling variable
$\text{XOther}_t$	=	SAE Other variable
$\text{DSM}_t^{\text{PastPgms}}$	=	Cumulative impact of past programs

Once the model is estimated, it can be used to generate a forecast without future programs by setting the forecast values for the DSM variable to equal the cumulative continuing impact of past programs<sup>4</sup>.

$$\text{Fcst}_t^{\text{NoFuturePgms}} = F(\text{DSM}_t^{\text{PastPgms}}, \text{XHeat}_t^{\text{Fcst}}, \text{XCool}_t^{\text{Fcst}}, \text{XOther}_t^{\text{Fcst}}) \quad (6)$$

where

$\text{XHeat}_t^{\text{Fcst}}$	=	SAE Heating variable
$\text{XCool}_t^{\text{Fcst}}$	=	SAE Cooling variable
$\text{XOther}_t^{\text{Fcst}}$	=	SAE Other variable
$\text{DSM}_t^{\text{PastPgms}}$	=	Cumulative historical and continuing impact of past programs

The model can also be used to generate a forecast with future programs by setting the forecast values for the DSM variable to equal the cumulative impacts of past and future programs<sup>5</sup>.

$$\text{Fcst}_t^{\text{WithFuturePgms}} = F(\text{DSM}_t^{\text{PastPgms}} + \text{DSM}_t^{\text{FuturePgms}}, \text{XHeat}_t^{\text{Fcst}}, \text{XCool}_t^{\text{Fcst}}, \text{XOther}_t^{\text{Fcst}}) \quad (7)$$

<sup>3</sup> In this paper, the discussion assumes that the DSM variable is a kWh value as illustrated by the red line in Figure 2. However, the DSM variable may also be represented as a kW or dollars invested value.

<sup>4</sup> The cumulative continuing impact of past programs is shown as the blue line in Figure 2 and Figure 3.

<sup>5</sup> The cumulative impact of past and future programs is illustrated by the green line in Figure 2.

## Incorporating DSM into the Load Forecast

where

$X_{Heat_t}^{Fcst}$  = SAE Heating variable

$X_{Cool_t}^{Fcst}$  = SAE Cooling variable

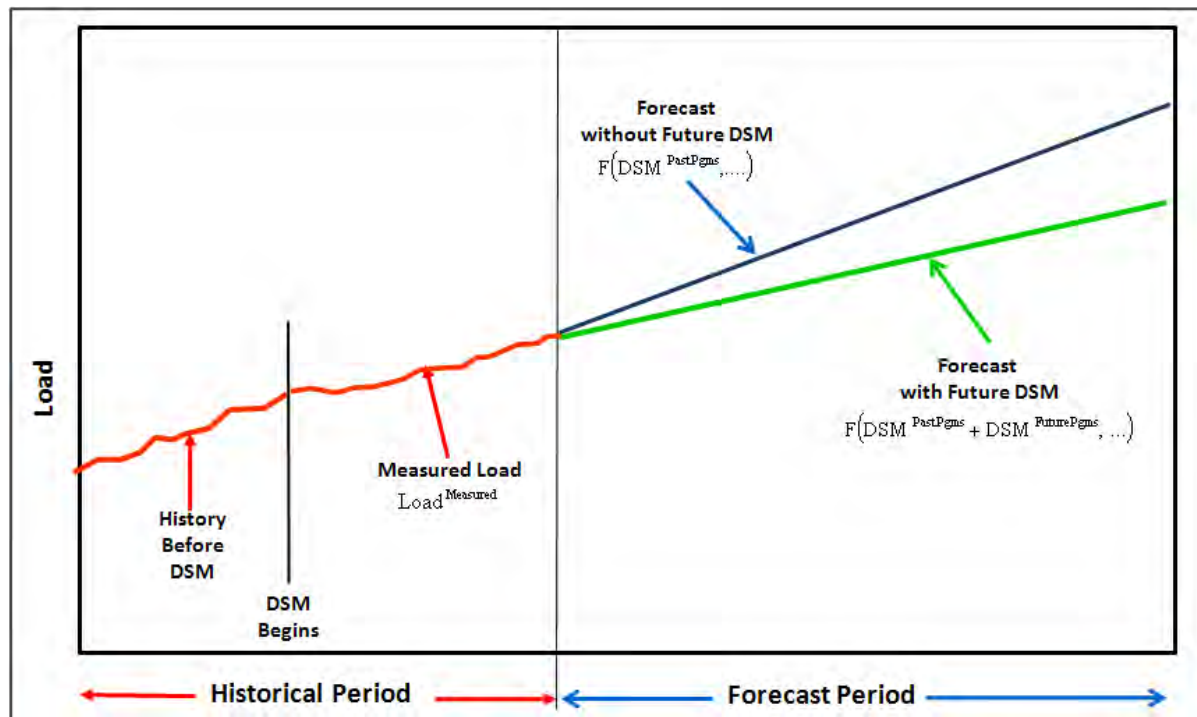
$X_{Other_t}^{Fcst}$  = SAE Other variable

$DSM_t^{PastPgms}$  = Cumulative historical and continuing impact of past programs

$DSM_t^{FuturePgms}$  = Cumulative impact of future programs

Figure 5 illustrates this method. The actual history (the red line) is used to estimate the forecast model parameters. The forecast model is then used to generate the forecast assuming only the cumulative impact of past programs, but no future DSM programs (the blue line). The forecast model is then used to generate the forecast with cumulative impacts of past and future programs (the green line).

**Figure 5: Method 2 Illustration**



In the estimated model, the coefficient on  $DSM^{PastPgms}$ , represents a statistical realization rate for the estimated DSM savings. If the estimated impacts of DSM accurately represent the savings over and above what otherwise would have occurred, then the coefficient should be close to -1.0. If the coefficient is smaller in absolute value (e.g., -.75), then the statistical model suggests that the actual realized DSM impacts are less than the program impact estimates. Ignoring the negative sign, the estimated coefficient is a statistical realization rate. By applying the estimated coefficient to the future program impacts, the modeler assumes that the realization rate for future program impacts is the same as it is estimated to be for past program impacts.



## Key Issues

Like Method 1, this method requires a set of accurate and consistently defined estimates for cumulative program impacts above market standards. However, the importance of accuracy is lessened by the estimation of the statistical realization rate. If program impact estimates are overly aggressive, a statistical realization rate should be less than 1.0. If program impact estimates are overly conservative, the statistical realization rate should be greater than 1.0. It is still important that the estimated impacts of past and future programs are defined consistently over time.

- Statistical Significance of the DSM Coefficient:** Statistical estimation of the DSM variable coefficient requires that there have been large and significant programs with impacts that vary over time. The impacts should be larger than the statistical noise in the data and different than the national level of impacts already included in the SAE variables. There is a danger that the DSM variable will be highly correlated with other variables which may make it difficult to identify the independent impact of the DSM variable. If the utility programs have been comparable to the regional efforts, the DSM variable would have an expected coefficient of zero in the model since the regional DSM impacts are already accounted for in the SAE variables.
- DSM Variations:** Using a single DSM variable assumes that the aggregate of DSM programs have a common realization rate. Of course, it would be possible to include multiple DSM variables, organized by program type or end-use. However, it is unlikely that this will produce statistically meaningful results because the disaggregated impacts will likely be small and collinear.

## Method 3: DSM Trend

Methods 1 and 2 make explicit efforts to adjust DSM out of the history and out of the forecast. Method 3 takes a different approach by recognizing that historical DSM and DSM trends are embedded in the actual sales data. Forecasting models that are built on these data implicitly assume that the levels and trends for DSM savings in the history continue into the forecast at approximately the same rate. As a result, the forecast only needs to be adjusted if DSM impacts are expected to be greater or less than the historical trends.

Like methods 1 and 2, this method requires cumulative DSM impact data for the historical period. Based on the historical impact of past programs, a simple trend model is implemented. For example, a simple linear model would have the form shown in equation (8)

$$DSM_t^{PastPgms} = b_0 + b_1 \times Time_t + e_t \quad (8)$$

where time is the simple trend variable that increases by 1.0 each year. While equation (8) shows a simple model, the model can be more complicated using trend shifts, seasonal trends, or perhaps nonlinear trend variables. The key is that the types of trend variables used here are consistent with the types of trend variables included in the estimated energy model.

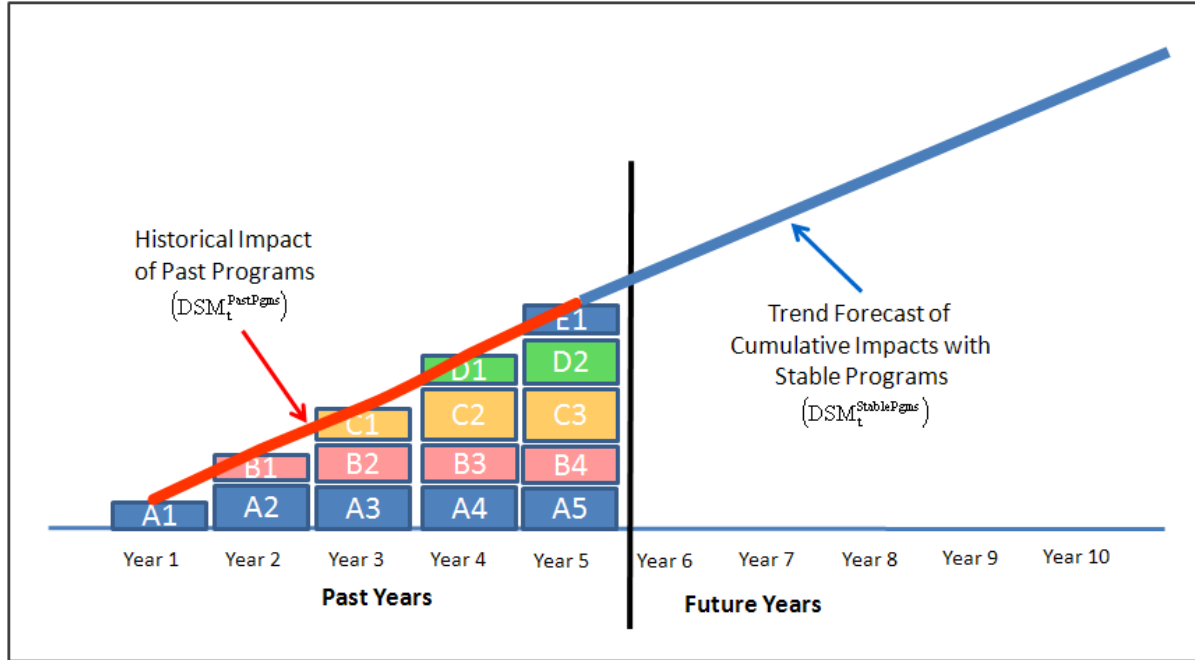
The estimated parameters of the DSM trend model (equation 8) can be used to develop a trend forecast for cumulative DSM impacts. This trend forecast (equation 9) assumes that program activity levels are stable, generating a relatively stable trend in the cumulative impact of past and future program.

$$DSM_t^{StablePgms} = \hat{b}_0 + \hat{b}_1 \times Time_t \quad (9)$$

This idea is depicted in Figure 6. The figure drawn assumes 5 years of historical DSM activity (program years A to E), and shows a 5 year extension of the cumulative trend line corresponding to equation (9). This is the DSM trend line ( $DSM_t^{StablePgms}$ ).

## Incorporating DSM into the Load Forecast

Figure 6: Method 3 – DSM Trend Analysis



The next step is to estimate a forecast model based on measured historical sales. This model would take the following general form:

$$\text{Load}_t^{\text{Measured}} = F(\text{XHeat}_t, \text{XCool}_t, \text{XOther}_t) + e_t \quad (10)$$

where

$F(\dots)$  = Forecasting model (e.g. regression model) with residual values ( $e$ )

$\text{XHeat}_t$  = SAE Heating variable

$\text{XCool}_t$  = SAE Cooling variable

$\text{XOther}_t$  = SAE Other variable

This is unlike equation (2) in Method 1 because the left hand variable has not been adjusted upward for DSM impacts. It is also unlike equation (5) in Method 2 because there is no DSM variable in the model. Once the model is estimated (10), it can be used to generate a forecast of energy use assuming continuation of DSM program impact trends as shown in equation (11).

$$\text{Fcst}_t^{\text{StablePgms}} = F(\text{XHeat}_t^{\text{Fcst}}, \text{XCool}_t^{\text{Fcst}}, \text{XOther}_t^{\text{Fcst}}) \quad (11)$$



where

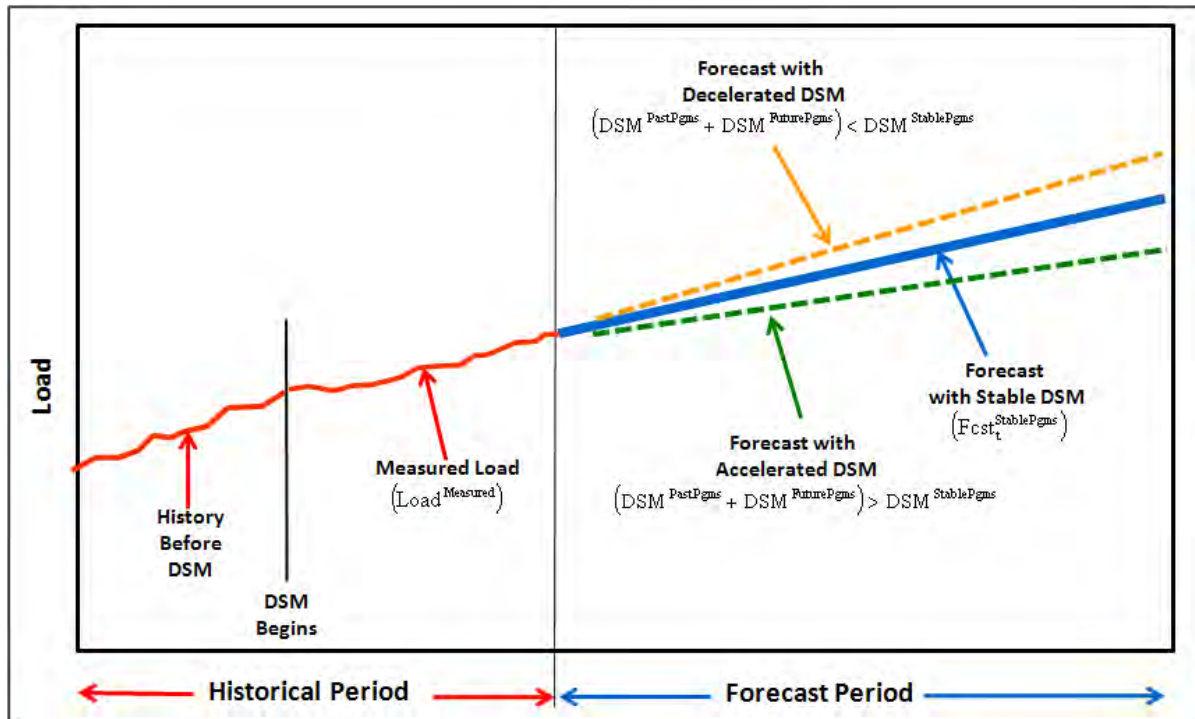
$XHeat_t^{Fest}$  = SAE Heating variable

$XCool_t^{Fest}$  = SAE Cooling variable

$XOther_t^{Fest}$  = SAE Other variable

The idea behind Method 3 is shown in Figure 7. The historical model is estimated with measured load data, as represented by the solid red line. The forecast is represented by the solid blue line ( $Fcst_t^{StablePgms}$ ). Because cumulative DSM impacts and their trends are embodied in the historical data, the projection of these data implicitly assumes that the trends in the DSM impacts will extend into the forecast period. In other words, the forecast (blue line in Figure 7) implicitly includes the DSM trend line ( $DSM^{StablePgms}$ ) developed in equation (9).

**Figure 7: Method 3 – Forecasts and Acceleration Adjustments**



In the final step of Method 3, the forecast is adjusted if the cumulative impacts of past and future programs are expected to accelerate or decelerate relative to the DSM trend line ( $DSM^{StablePgms}$ ). For example, if the DSM trend line forecast is forecasting 100 MWh in a future year and the cumulative impact of past and future programs are expected to be 120 MWh in the same future year, the forecast should be adjusted downward 20 MWh. In this method, the forecast is adjusted up or down by the difference between the DSM trend line and the cumulative impact of past and future programs.

If the total cumulative impact of past and future programs is expected to fall short of the historical trend, then the energy forecast should be adjusted upward by the amount of the deceleration below the DSM trend line. This adjustment is represented by the following final energy forecast equation (12).

## Incorporating DSM into the Load Forecast

$$\begin{aligned} Fcst_t &= Fcst_t^{StableDSM} + DSMAcceleration_t \\ &= Fcst_t^{StableDSM} + \left( DSM_t^{PastPgms} + DSM_t^{FuturePgms} - DSM_t^{StablePgms} \right) \end{aligned} \quad (12)$$

This equation starts with the model forecast from equation (11) and adds in the estimated program acceleration (positive or negative) relative to trend.

If program plans call for continued steady program efforts through time, Method 3 is a convenient approach. In this case, DSM acceleration is expected to be zero, and the forecast from equation (11) is the final energy forecast.

## Key Issues

This method requires the same historical DSM impact data as Methods 1 and 2. However, like Method 2, the accuracy of these estimates is reduced due to the resulting modeling of the DSM trend. Nevertheless, it is still necessary to understand the historical impact of past DSM programs. In Method 3, these data are used to develop the DSM cumulative impact projection (as shown in Figure 6). Issues with this method are as follows.

- **Misses Lifecycle Effects:** Using the trend model, the assumption is that cumulative DSM savings grow linearly over time (assuming a linear trend model is used). This is often not the case since the the focus of DSM programs changes over time and since different technologies have different measure lives. Explicit impact accounting will more accurately represent the duration of past and future impacts as they enter the stream of cumulative impacts. In addition, long-run linear growth requires program acceleration to insure that new impacts from future programs counteract the drop off of decaying impacts from older programs.
- **DSM Growth Trend Complexities:** As shown in equations (8) and (9), the trend model has a single coefficient on time resulting in linear growth of cumulative DSM impacts through the forecast period. This assumption may be valid if DSM efforts are expected to be relatively stable or gradually increase through time. However, programs are generally ramped up and down through time as end-use technologies, efficiency standards, and market conditions change. Further, the annual profiles of DSM impacts will be different for major end-use groupings such as heating, cooling, and lighting. Considering the complexity of DSM program implementations, equations (8) and (9) may need to be modified to reflect these effects. These differences will be important for monthly sales forecasting and peak load forecasting.
- **DSM Trend Assumption:** The DSM trend line is a statistical attempt to capture the underlying trend in the SAE model. To the extent that the SAE model contains binary shift variables or end-shift variables, the DSM trend line may not realistically represent embedded DSM in the SAE model.

## Conclusions

When using an econometric or SAE model, historical DSM investments influence the historical sales data, the forecast model parameters, and the resulting sales projections. As DSM investment increases, forecasters need to adjust their sales forecasts to account for this acceleration relative to the historic DSM that is implicitly included in an unadjusted forecast.

We have considered three methods for recognizing past DSM and adjusting the forecast for future DSM. In all methods, the forecaster initially needs to develop the cumulative impacts from past and future DSM program (Figures 1 and 2). Once the DSM data series are developed, the forecaster may explore the benefits of each method.





### **Method 1, “Add Back” Method**

Method 1 attempts to reconstitute load by adjusting the left-hand-side of the SAE model to create a model without DSM. Once the model is developed, the forecast is adjusted to account for past and future DSM impacts. This method appears to work well in situations where there is a short history of minor DSM investments, and the historical impacts can be reconstituted from program data.

### **Method 2, “DSM Variable” Method**

Method 2 attempts to model DSM by inserting a variable on the right-hand-side of the SAE model. Once the model is developed, the forecast is created by inserting a forecast of the cumulative impact of past and future programs. This method requires that historical programs have had a major impact on historical sales and that there is enough independent variation in the impact history to generate statistically significant parameters.

### **Method 3, “DSM Trend” Method**

Method 3 attempts to capture the underlying DSM trend without adjusting either the right or left-hand-side of the SAE model. Assuming that the DSM trend is obtainable, the forecast is adjusted for net changes from the DSM trend line. This method is well suited to a situation where there has been a longstanding and relatively stable DSM history and where there is expected to be significant acceleration or deceleration of program activity.

Because each utility situation is unique, the methods should be explored and selected based on the availability of data and the forecaster’s objectives.

## Glossary

In this paper, key DSM terms are used to articulate the development of data for use in the forecasting methods. These terms are used consistently throughout the paper and do not represent formal definitions used throughout the electric industry.

### Cumulative Impact

In this paper, the **cumulative impact** in a year means the DSM savings that occur in that year resulting from programs in that year and all past years. In Figure 2, the cumulative impact is shown as the vertical sum of a column. For example, in Year 3, the cumulative impact of Programs A, B, and C is represented by the blocks labeled  $A3 + B2 + C1$ . Cumulative impacts may apply to the historical impacts of past programs, the continuing impact of past programs, and the impact of future programs.

### Historical Impact of Past Programs

The **historical impact of past programs** is the realized DSM savings from implemented programs in past years. In Figure 2, the historical impacts are shown in blocks A1 through A3, B1 through B2, and C1. These impacts may also be shown as cumulative impacts. The cumulative impacts associated with these programs are shown by the red line in Figure 2.

### Continuing Impact of Past Programs

The **continuing impact of past programs** is the future DSM savings expected from programs that were implemented in past years. In Figure 2, program A begins in Year 1. The savings from this program will continue throughout the measured live of the DSM technology. While Years 1 through 3 represent historical years, Year 4 represents the beginning of the future. The continuing impact of program A is the expected DSM savings beginning in Year 4 and is represented by blocks A4 through A8. These impacts may be cumulative when added with the expected savings of other program (B and C) that have been implemented in the past.

### Cumulative Impact of Future Programs

The **cumulative impact of future programs** are the future DSM savings expected from future programs. In Figure 3, future programs begin in Year 4 and are represented by the green squares. The cumulative impact of future programs is the vertical sum of the green squares in a single year. For example, in Figure 3, Year 6, the cumulative impact of future programs is  $D3+E2+F1$ . These impacts exclude credits for market transformation.

### Cumulative impacts past and future DSM programs

The **cumulative impact of past and future programs** are the DSM savings across both historical and future programs measured in a single year. In Figure 3, this impact is represented by the solid green line at the top of the impact stack in each year. In this paper, these impacts generally exclude credits for market transformation.



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