REPLY COMMENTS OF DUKE ENERGY INDIANA REGARDING THE COMPANY'S 2015 INTEGRATED RESOURCE PLAN

I. Introduction

On November 2, 2015, Duke Energy Indiana submitted its 2015 Integrated Resource Plan ("IRP"). Although the IURC's proposed IRP rules are not yet final, Duke Energy Indiana has attempted to follow the process and requirements embodied in the draft rules. The Company's process included a four-meeting stakeholder engagement process in which the Company and participants discussed the methodologies and assumptions utilized in the IRP modeling and the results of that modeling prior to finalizing the IRP. Duke Energy Indiana seriously considered and responded to stakeholder comments throughout the process, as documented in the IRP. In accordance with the proposed IRP rules, additional comments have been received from the IURC's Director of Research, Policy and Planning, Dr. Bradley Borum, and a group of stakeholders – the Citizens Action Coalition of Indiana, Earthjustice, Indiana Distributed Energy Alliance, Michael A. Mullett, the Sierra Club and Valley Watch. Duke Energy Indiana is providing responses to both sets of comments in this document.

II. Duke Energy Indiana's responsive comments to Dr. Brad Borum's May 20, 2016 Draft Report

Dr. Borum's Draft Report sets forth specific issues and questions for Duke Energy Indiana to address.

A. Risk Assessment

Commission Questions – p. 5-7:

1. Are we correct that only three scenarios were fully optimized (page 111 and page 130 of the Technical appendix)?

2. Could the second three scenarios, where combined cycle units were substituted for combustion turbines, be characterized as sensitivities rather than scenarios [page 111]? If our characterization is accurate, then in retrospect, would Duke agree the selection of just three true scenarios for optimization may not have been sufficient to robustly reflect the risks Duke identified?

3. After the IRP modeling was done and Duke selected a preferred case (page 19) based on the carbon tax, which is different from the no carbon regulation case that might have normally been regarded as a base case (Business as Usual), were either of these scenarios initially optimized with some customer-owned resources such as combined heat and power, wind and solar renewables, and additional EE hardwired? Was any further optimization conducted?

4. Given that the first combined cycle generating unit in the preferred plan would be constructed in the relatively near-term (4 to 5 years or so – see page 13), does Duke anticipate any changes or actions to influence the timing or operating characteristics of the combined cycle, such as more EE, more demand response, or encouraging more customer-owned resources?

5. It appears that Duke may have unduly constrained the amount of EE prior to being analyzed in the System Optimizer. If the perception is accurate, it raises the concern that Duke might not have been able to deploy additional cost-effective EE and demand response to influence the timing and size of future resources such as the potential for a combined cycle unit in the near term and in the longer term as Duke's need for resources increases. That is, it appears that Duke limited the amount of EE and demand response by assuming the composition and size of the future annual EE portfolio impacts were the same after 2018 (page 76-77 of the IRP). Is this an accurate characterization?

6. If Duke believes our understanding of the treatment and characterization of EE and demand response are not accurate, we would welcome Duke's response. For future IRPs, and to be consistent with concerns raised by the Joint Commenters [on page 2], involving stakeholders in the development of scenarios, assumptions, review of data, methodological treatment of EE, and other resources might avoid misunderstandings and unnecessary controversy. The director also agrees with Joint Commenters that involving stakeholders in more in-depth reviews of the results may improve confidence in the credibility of the results. A better understanding by all also would benefit proceedings before the Commission.

7. The IRP States on page 9 that retirement analysis for the generation fleet was included in the overall optimization modeling. What is meant by "included in the overall optimization modeling?" How was this done? The description of the portfolios on pages 137-139 indicates that many retirements of generation units were assumed rather than optimized by the model. So, is this a contradiction?

8. On pages 104-105, Duke notes the assumed retirement date for Wabash River units 2-5 is 2016. Duke then goes on to say Unit 6 continues to be evaluated for natural gas conversion and that no decision has been made. However, all the Scenarios considered by Duke on pages 137-139 show Unit 6 retiring in 2016. Question: If no decision has yet been made regarding Unit 6, then why do all the scenarios show Unit 6 as retiring in 2016?

<u>Duke Energy Indiana Response to Risk Assessment Issues:</u>

1. To respond to the concerns about optimization , it may be helpful to revisit how Duke Energy Indiana defines Scenarios and Portfolios for resource planning purposes:

    - Scenarios are plausible views of what the world might look like over the next 20 years centered on Economic, Policy/Regulatory, Customer and Technology trends. Key modeling inputs associated with each scenario are load growth, fuel and power prices, emission allowance prices, as well as the capital costs and operating characteristics of new resource options.
    - Portfolios are the mix of resources, both existing and new, required to serve customer energy needs

    Given these definitions, in the 2015 IRP, Duke Energy Indiana utilized seven different scenarios: (1) No Carbon Regulation, (2) Carbon Tax, (3) Proposed Clean Power Plan, (4) Delayed Carbon Regulation, (5) Repealed Carbon Regulation, (6) Climate Change and (7) Increased Customer Choice. These seven scenarios and a stakeholder portfolio development exercise were used to produce nine portfolios: (1) No Carbon Regulation Portfolio, (2) Carbon Tax Portfolio, (3) Proposed Clean Power Plan Portfolio, (4) No Carbon Regulation Portfolio with additional CC, (5) Carbon Tax Portfolio with additional CC, (6) Proposed Clean Power Plan Portfolio with additional CC, (7) Stakeholder Distributed Generation Portfolio, (8) Stakeholder Green Utility Portfolio, and (9) High Renewables Portfolio.

The first three portfolios were the result of fully optimizing the model using the model inputs for the first three scenarios. Full optimization included selection of new conventional and renewable generation, energy efficiency programs and retirement of existing assets.

The second three portfolios substituted 448MW of combined cycle ("CC") capacity for 416MW of combustion turbine ("CT") capacity. This was done in order to examine the tradeoffs between cost, dependence on market purchases to serve customer energy needs and total CO_2 emissions when selecting a CC resource versus a CT resource for meeting capacity needs.

The two stakeholder defined portfolios were created using the results of the portfolio design exercise during our June 4, 2015 meeting. As the mix of assets was specified by stakeholders, these portfolios could not be optimized by the capacity expansion model.

The high renewables portfolio was fully optimized using a 25% lower cost for wind and solar technologies with the remaining inputs tied to the Carbon Tax Scenario.

2. As discussed in the response to question 1, the first three portfolios were fully optimized as was the high renewables portfolio. The two stakeholder specified portfolios and the three portfolios with the additional CC included were not fully optimized by the capacity expansion model. We believe that testing the performance of the nine portfolios across all seven scenarios does reflect a robust risk analysis effort. Additionally, multiple sensitivity runs were performed by varying individual model inputs within each scenario. In total, the 63 model runs of each scenario-portfolio pair as well as over 120 sensitivity runs provide an in depth analysis of the uncertainty Duke Energy Indiana faces in future resource decisions.

3. The initial portfolios for both the Carbon Tax Scenario and No Carbon Regulation Scenario were fully optimized with regard to combined heat and power, wind and solar, and EE. The portfolios with added combined cycle capacity took these optimized portfolios and simply substituted ½ of a combined cycle plant (448MW) for 2 combustion turbines (416MW). As the size and timing of resource substitution was closely maintained, further optimization was not performed. As discussed in the IRP document and during the stakeholder meetings, the purpose of these modified portfolios was to observe the tradeoffs between total cost (PVRR) and the degree to which the portfolios depended on market purchases to serve customer load. It is our view that a high dependence on market purchases to serve customer energy needs could represent a significant risk of price volatility to customers.

4. We continue to evaluate the key drivers behind the identified need for combined cycle capacity on an ongoing basis. Many factors will influence the exact size and timing of any potential request to add this capacity including updated load forecasts, changes to DR and EE projections, renewable assumptions and new customer-owned resources. Retirement plans for existing resources is also of significance. The net impact of all these factors will determine the size and timing of any proposed resource addition.

5. The Duke Energy Indiana IRP model did not limit the amount of EE and demand response in any year of the analysis. To lessen any confusion, the group of lowest cost EE bundles will be collectively referred to as the Base DSM Portfolio and the higher cost EE bundles will be collectively referred to as the Incremental DSM Portfolio. The first bundle of the Base DSM Portfolio was used to seed the process, but it was not hardwired into the plan. The IRP analysis was allowed to determine if the first bundle would be selected for inclusion (and it was in all portfolios). Future bundles of the Base DSM Portfolio, which the model selected in all cases, were also based on a combination of the 2015 approved DSM portfolio, the 2016-18 proposed DSM portfolio and an expectation that the EE programs in 2019 would provide the same overall EE impacts as 2018. However, and this needs to be emphasized, the model was also presented with additional EE in the Incremental DSM Portfolio, which the model did not always choose. The fact that the bundles in the Base DSM Portfolio were created using an assumption of continuing the same general composition and size of the 2018 DSM Portfolio did not in any way limit the IRP model's ability to choose more EE if the Incremental DSM Bundle was a better alternative than other resources.

   Because these underlying DSM portfolios, 2015 and 2016-18, were required to be cost-effective per the IRP rules, this proxy portfolio was evaluated for cost effectiveness, but this was not used as a means to reduce the ability of the IRP to select EE programs. As explained in the IRP, this first Base Bundle was only a starting point for the creation of a set of additional EE bundles to be evaluated by the IRP. In order to create a starting point for the IRP analysis, Duke Energy Indiana used the currently approved 2015 and the proposed 2016-18 portfolio as a proxy for a reasonable portfolio that was proven to be accepted in the marketplace and was feasible to implement. However, this proxy portfolio was only one out of multiple bundles of EE from which the IRP process was allowed to select in the analytical process. As stated, it was not hardwired into the plan. In addition, the use of a portfolio that was based on the proposed 2016-18 portfolio had no impact on limiting the amount of EE that was ultimately chosen by the IRP, because other incremental bundles were also available for selection by the IRP process. By letting the IRP model determine if it would select the existing portfolio of proven and proposed programs, Duke Energy Indiana is able to confirm that the portfolio is cost-effective within the context of the IRP. This is information that would be important to the Company as a check on the current portfolio. Then, once that portfolio is selected by the IRP process, as a starting point, it makes sense to provide additional incremental proposed bundles of EE that represent similar overall programs and technologies, but not specific measures. Due to the uncertainty around future changes in technology, changes in efficiency baselines, etc., it is not reasonable to focus on any specific measure that might, or might not, be implemented as part of an incremental proposed bundle of EE. Rather, it is important to focus on the overall impact that a bundle of measures will have on future energy and demand forecasts. These incremental proposed bundles were created and provided as additional EE options for the IRP to choose, or not.

6. As stated above, Duke Energy Indiana does not believe that the understanding of the treatment and characterization of EE and demand response by the Joint Commenters is accurate. The IRP modeling was not constrained from choosing additional EE resources, therefore, the objective of modeling EE as a resource on an equal basis with other resources was met in this IRP. Duke agrees that additional stakeholder involvement in future IRP processes might improve the understanding of the assumptions and treatment of EE as a resource and this recommendation will be incorporated into the future IRP stakeholder process.

7. For the 2015 IRP, the model runs were conducted to allow economic retirement of existing generating units if the software (System Optimizer) determined that to be the least cost option during optimization runs. This was accomplished by including avoidable ongoing capital, fixed and variable O&M, and fuel costs. The model was then allowed to continue to run the existing units or retire and replace them with generating resources it determined to have a lower total cost over the modeled study period. The portfolio descriptions identifying the retirements "as assumed" is accurate for the oil-fired CTs (Miami-Wabash and Connersville) and Gallagher Units 2 and 4. The retirement date of the CTs was determined by previous regulatory settlements and the potential retirement of Gallagher Station was assumed through a separate retirement analysis conducted prior to IRP modeling relying on assumptions around future environmental rules and regulations. For the remainder of the existing units, the description as "assumed" is an incorrect characterization as these retirements (or not) were determined through the model optimization process as described above.

8. At the time of the 2015 IRP, no decision on the Wabash River Unit 6 natural gas conversion had been made. The reason that all portfolios showed Unit 6 as retiring was because Unit 6 had to stop burning coal as of April 15, 2016 under the MATS rule (Wabash River received a one year extension from the MATS compliance date). Given that Unit 6 could not continue burning coal and no decision had been made regarding a conversion to natural gas, it was shown as retired. In addition, the natural gas conversion of Wabash River Unit 6 was a resource option in the 2015 modeling, but was not selected as part of an optimized portfolio.

B. Constructing, Evaluation, and Integrating DSM Bundles

Commission Comment – p. 7:

It was not clear how Duke constructed the bundles of EE and demand response resources. Moreover, because many of the resource portfolios were predetermined, meaning they were not the result of optimization, it is not clear how the EE and demand response bundles would have been optimized to treat EE and demand response as resources on as comparable a basis as possible to any other resource.

<u>Duke Energy Indiana Response:</u>

Simultaneous optimization did occur in the modeling because the IRP model was given the opportunity to select from multiple bundles of EE. Said another way, the IRP model had the option to choose bundles of EE from the Base DSM Portfolio, which the modeling results show that the IRP model always selected in every scenario. The IRP model was also given the option of choosing additional bundles from the Incremental DSM Portfolio and the modeling results show that, in general, the model did not choose additional EE in the first 10 years of the IRP; however, the model did choose incremental additional EE in the later years in most cases. Duke Energy Indiana does agree that the modeling process could potentially be modified in the next IRP process by offering the model additional granularity in the Incremental DSM Bundles, i.e. the ability to select additional EE at the Program level rather than the Portfolio level and that potential modification is discussed further below.

Commission Comment – p. 8

1. Duke's explanation of the "Measure of Life" treatment of existing EE ("roll off") seems to be an improvement in the 2015 IRP. However, the write-up is not as detailed or as clear as it could be to allow the reader to better understand how the roll off effects are modeled and how this method impacts the load forecast and the resource analysis. Additional clarity about how the statistically adjusted end-use (SAE) models (and other analysis) capture the roll off effects; how these effects are replaced with the naturally occurring EE, and how new EE is incorporated without the potential for over-estimating (double counting) or underestimating is necessary. (page 35).

- *a. A specific numerical example would help to clarify how Utility EE effects are being rolled off. What is an accelerated benefit (page 35)? How is the accelerated benefit calculated or estimated? How is it determined when the energy reduction would have otherwise occurred?*
- *b. What are naturally occurring appliance efficiency trends that replace the rolled-off UEE benefits (page 35)? How are these naturally occurring trends determined or developed? Is it always the result of new appliance or equipment standards going into effect, or can there be another driver?*
- *c. Page 135 contains a section titled "Identify and Screen Resource Options for Future Consideration." However, the section includes this sentence: "Projected impacts from both Core and Core Plus EE programs were included." What does this sentence mean? How were these projected impacts included?*

<u>Duke Energy Indiana Response:</u>

a. "Accelerated benefits" refer to energy usage reductions achieved as a result of the Utility Energy Efficiency ("UEE") efforts. Absent these efforts, the efficiency reductions would not have occurred for a period of years later as a result of natural increases in efficiency. Accelerated benefits are based on program activity estimates. The naturally occurring energy reductions are based on the efficiencies forecast by the EIA for the West North Central region. An example is charted below (labeled "Figure 1") in which there is an assumed 100 MWh "savings" as a result of UEE programs. Assuming an approximate 7 year average measure life for this example, the UEE savings is "rolled off" in years 5 through 9, as the naturally occurring efficiencies are expected to “roll-on” by means of incorporating the naturally occurring efficiencies in the end use models (i.e., SAE and the load forecast).

b. Natural trends are based on forecast data for end-use efficiency (and market penetration) as provided by the EIA. They reflect increasing efficiency trends. EIA is capturing these efficiency trends resulting from new motor standards, building codes, etc., and reflect the efficiencies in lighting, heating and cooling end uses, as well as “miscellaneous” end-uses that are meant to incorporate ever-changing technologies to the extent that they can be predicted. As shown in the example below, naturally occurring efficiencies replace the “rolled-off” UEE efficiencies.

c. After review, Duke Energy Indiana reasonably believes that the sentence noted above was inadvertently retained from a prior version of the IRP. It was an error and impacts from “Core and Core Plus EE programs” were not included.

Year	0	1	2	3	4	5	6	7	8	9	∑
Accelerated UEE Benefit		<100>									
“Roll Off”			0	0	0	10	20	40	20	10	100
Cumulative EIA Efficiency relative to trend						<10>	<30>	<70>	<90>	<100>	
Mwh effect on Forecast	0	<50>	<100>	<100>	<100>	<100>	<100>	<100>	<100>	<100>	

Figure 1: Example of UEE achievement and roll-off of benefits in ensuing years, expressed in terms of impact to MWH forecast.

Commission Comment – p. 8

2. *The IRP notes on page 45, for the period 2016-2018, that the portfolio reflects the EE programs that were filed for approval in Cause No. 43955-DSM3 for the period 2016-2018 and were locked-in.*
   a. *Would Duke agree that, because these programs were not yet approved, these EE programs were too speculative to be hardwired?*
   b. *If so, would Duke also agree that, as a result of hardwiring these programs, the models were prevented from objectively selecting and optimizing these EE programs in relation to other resources?*
   c. *Even if the objective was merely to see how much results changed, would it be useful to Duke and stakeholders to examine the optimized results?*

Duke Energy Indiana Response:

a. As noted above, the EE programs were not "locked-in", but rather were permitted to be selected as part of an optimized model run.

   In order to create a portfolio of DSM measures to be evaluated in the IRP process, Duke Energy Indiana chose to include the proposed set of measures, along with the approved measures for 2015, as a starting point for the process; however, the inclusion of these measures was only intended to be an initial Base bundle of DSM to introduce into the process to be evaluated in the IRP models.

   The selection of this particular set of measures was based on a detailed understanding of the impacts and program costs created for the purpose of the Company's DSM3 filing. The use of the term "hardwired" or "locked-in" in this context is not accurate because this proposed portfolio represented a set of measures that the IRP process was allowed to evaluate on an equal basis with other resources. Further, additional bundles of measures were also presented to the IRP process for evaluation. The fact that the IRP process models chose the original proposed Base bundle in all cases indicates that this portfolio was an acceptable part of a cost effective resource portfolio. To characterize it as being "hardwired" or "locked-in" would imply that this was the only DSM or other resource alternative presented to the IRP process for selection. That was not the case.

   By letting the IRP model determine if it would select the existing portfolio of proven and proposed programs, Duke Energy Indiana is able to confirm that the current portfolio is cost-effective within the context of the IRP. Then, once that portfolio is selected by the IRP process, as a starting point, it makes sense to provide additional similar proposed Incremental bundles of EE; although, they were not identified as specific measures. The Incremental bundles of EE were created and provided as additional EE options for the IRP to choose, or not, based on its optimization process.

   At some level, a Base DSM portfolio with a certain minimum size must be selected as a starting point DSM resource that the model could select or not select depending on economics, and Duke Energy Indiana chose to use the existing and proposed portfolios as that starting point.

b. The concept of "optimized" results is confusing in this context. If the intent of the IRP exercise was to allow the model to choose as much DSM as possible, then the Duke Energy Indiana approach accomplished that objective by using the concept of a Base DSM Portfolio (which happened to be the same as the existing and proposed portfolios) and an Incremental DSM Portfolio, each of which were available to be selected by the IRP assuming it was preferable to building new generation.

c. Duke Energy Indiana does not object to the concept of sharing the modeling results with stakeholders as long as the process does not interfere with the timely completion of the final IRP.

Commission Comment – p. 9

3. The director agrees with the Joint Commenters (page 2) that Duke should provide more detail on the assumptions used and the data supporting the EE effects on Duke's load shapes. The written discussion of how the new DSM bundles were constructed, analyzed, and integrated into the IRPs (in a manner that is comparable to other resources) would benefit from more detail and clarity including, as the Joint Commenters observed, information as to how the screening process was conducted. Also, it is awkward to have to go back and forth between the information contained in the IRP and the Technical Appendix to try to understand how the bundles were created.

a. For future IRPs and recognizing the difficulties, would Duke consider providing sufficient relevant information contained in the public version of the IRP to enable the reader to have a basic understanding and provide more detailed information in an appendix?

b. Would Duke please provide additional detail on how Duke gets from Potential DSM, as reflected in a market potential study, to the DSM that is included in the IRP analysis?

<u>Duke Energy Indiana Response:</u>

a. Yes, Duke Energy Indiana appreciates this feedback and will include more detail in future IRPs

b. The Economic Potential DSM from the Market Potential Study was used as an upper limit to the overall size of all of the Base and Incremental Bundles combined, which was not reached by any of the IRP model scenarios. The methodology used by Duke Energy Indiana was not to start with the overall Technical Potential and work backwards, but rather to start with a well-known set of programs and build upwards. By starting with a set of bundles in the Base DSM Portfolio, allowing the IRP to decide if it would choose those bundles and then also providing, at the same time, a set of Incremental DSM Bundles and allowing the IRP to determine if those Incremental DSM Bundles would be chosen, the IRP model was allowed to solve for an overall portfolio of DSM that was properly sized relative to other resources.

Commission Comment – p. 9

4. Because of the increased importance of DSM and in advance of the rulemaking, there is a need for added clarity.

a. What is the basis or rationale for using the assumption that Duke will be implementing the currently approved and proposed portfolio of EE programs throughout the IRP analysis period (on page 76)?

b. How were the sub-portfolios developed? There is no discussion of how this was done, such as the data, assumptions, costs, etc.

c. What are the implications of this assumption?

d. Did Duke consider alternative assumptions? If yes, what were they, and why were they not used? How was technological change considered in developing the sub-portfolios?

<u>Duke Energy Indiana Response:</u>

a. As stated before, the assumption of continuing to implement the approved and proposed portfolios was simply a starting point for the purpose of providing a portfolio of DSM measures for the IRP to evaluate on the same basis as other resources. Duke Energy Indiana fully expects that the composition of the programs and measures that are eventually implemented in the future will be different than what was included in the proposed portfolios; however, it would be difficult to impossible to attempt to project a more granular level or composition of individual DSM measures beyond the first 3-5 years of the current filing period. It is important to note that the goal of the modeling exercise should be to provide a set of DSM programs that are reasonable and properly valued rather than to attempt to project an exact set of expected DSM measures up to 20 years in the future.

b. <u>Base DSM Portfolio</u>. The Base DSM sub-portfolios were created using the assumption that the Company would be implementing the same types of programs and measures as the currently approved portfolio of EE programs in 2015 and the portfolio of EE programs proposed in Cause 43955 DSM3 for the period of 2016-18. For periods beyond 2018, the assumption was made that the composition and size of the future annual DSM portfolio impacts were similar to the 2018 portfolio. For the analysis period, the 25 year projected Base DSM Portfolio was also divided into 5 sub-portfolios, each with five years of new additional program participants. The impacts from each of the sub-portfolios and the revenue requirements necessary to achieve those impacts were treated as stand-alone resources available to be chosen in the IRP process.

   The reason for selecting a 5 year minimum period for each bundle was that, as a practical matter, DSM programs cannot be started and stopped on short notice and the 5 year period is a logical period of time for designing and implementing a bundle of DSM programs.

   <u>Incremental DSM Portfolio</u>. In order to create an Incremental DSM Portfolio for potential selection by the IRP, the programs in the Base DSM Portfolio were assumed to be augmented with additional participants through increased program expenditures to achieve additional KWh savings.

   The Incremental DSM sub-portfolios were created using the assumption that additional participation would be obtained for the same types of programs that exist in the Base DSM Portfolio, with the exception of programs that are already designed to reach the entire eligible population in the Base DSM sub-portfolio (e.g., My Home Energy Report program) or programs where the market is expected to become fully saturated in the Base DSM sub-portfolio (e.g., certain CFL lighting measures). During the IRP analysis period, the Incremental DSM portfolio was divided into 5 sub-portfolios, each with 5 years of new additional program participants. Impacts from each of the sub-portfolios and the revenue requirements necessary to achieve those impacts were treated as stand-alone resources available to be chosen in the IRP process.

The Incremental DSM Portfolio was initially sized to include additional impacts equal to 50% of the Base DSM Portfolio for each program and/or measure with the exception of those listed above. Analysis of this proposed “50% bigger” Incremental DSM Portfolio showed that the IRP models did not choose it in any of the scenarios. Therefore, another smaller, less expensive Incremental DSM Portfolio, structured in the same manner as the original Incremental DSM Bundles, was created to include 25% of the impacts of the Base DSM Portfolio with correspondingly lower revenue requirements, including lower expected cost growth rates in future years, for potential selection by the IRP process. This smaller, less expensive Incremental DSM Bundle was chosen in some of the optimized portfolios in the later years of the IRP study period.

Revenue Requirements. In order to estimate the revenue requirements necessary to implement both the Base and Incremental DSM Portfolios, one issue that needed to be addressed was whether the program implementation costs are affected by the level of market penetration. In other words, as more of the market potential is achieved through the implementation of the EE programs, one would expect that the unit cost to achieve the next increment would increase. Information in the EE literature defining the relationship between program costs and market penetration is lacking.

Recently, the Company obtained a research study[1] authored by Dr. Richard Stevie of Integral Analytics that relies on state level data from the Energy Information Administration. The study examined the relationship between spending on energy efficiency programs and the level of first year impacts from the implementation of energy efficiency programs as well as the cumulative level of impacts. The study concluded that energy efficiency program costs per kWh increase with increases in cumulative achievement of market potential as measured by the percent of retail kWh sales. Based upon this study, annual rates of growth in the unit Program Costs were estimated at 3.79% for the Base DSM Portfolio and 0.72% to be applied to a stepped up starting unit cost for the Incremental DSM Portfolio. The stepped up starting unit cost for the Incremental DSM Portfolio reflects an expected higher cost to acquire additional program participants.

In addition to the cost increases required to increase participation in existing programs, a significant component of current Base DSM Portfolio, the CFL lighting measures in the Portfolio, is expected to be fully depleted (meaning the market will be saturated) in the Base DSM Portfolio, and therefore not available in the Incremental DSM Portfolio. With the change in standards due to the Energy Independence and Security Act and the market transformation that has already occurred, and is expected to continue in the future, programs that incentivize the installation of CFL bulbs will no longer be viable at levels above the current Base DSM Portfolio and will not be offered in the Incremental DSM Portfolio. The Company has already begun replacing CFL bulbs with LEDs in several programs; however, the incremental savings gained by moving from a CFL to an LED are much lower than moving from an incandescent to a CFL.

[1] The research study is included as Attachment 1.

Because these CFL programs are very low cost and will no longer be available, the incremental difference in impacts required to reach higher levels of impacts set forth in the Incremental DSM Portfolio must be made up through increased participation in more expensive measures, also resulting in an increase in the average incremental cost per KWh at the portfolio level.

Finally, the My Home Energy Report was designed to reach the entire available market in the Base DSM Portfolio and incremental participation and impacts are not projected to be available from these programs.

c. By assuming a set of Base DSM Portfolio bundles that are based on current experience Duke Energy Indiana was able to better project the cost of these Base DSM Bundles into the future using the methods described above. Further, by treating the Incremental DSM Bundles as an extension of these Base DSM Bundles, Duke Energy Indiana was better able to project the costs of implementing additional amounts of EE. Using any other method would have introduced a level of uncertainty related to program design, cost and customer acceptance that could not be analytically justified.

d. The initial approach that was considered by Duke Energy Indiana was to attempt to model each bundle as a stand-alone set of measures on an annual basis; however, this approach was not chosen based on further consideration of the practical implications of deploying a set of DSM programs in the marketplace. For example, assume that the IRP analysis had chosen a particular DSM program in a given future year, say 2021. However, if that same analysis had determined that that same program was not selected for 2022 but then was again selected in 2023, the actual deployment of a DSM measure using that schedule would be highly impractical, because the program would have to be deployed in 2021, suspended in 2022, and then re-deployed in 2023. This type of schedule would result in significant extra costs for starting and stopping a program as well as a poor customer experience when, simply due to the timing of their interest in participating, a customer could potentially be told that a program was no longer available, or that they would have to wait another few months or years to participate.

As for technological changes, Duke Energy Indiana used a methodology that assumes a bundle of DSM measures at a particular cost per unit in some future year. However, this methodology was never intended to imply that the exact same measures that are currently offered would always be exactly the same measures offered in the future. By choosing to model a generic set of programs with a commitment to a certain level of impacts at a certain cost, this methodology inherently accommodates expected changes in technologies in the future.

Commission Comment – p. 9-10

5. *Duke states on page 77 that the incremental sub-portfolios were created using the assumption that additional participation would be obtained for the same programs that exist in the base portfolio but that there are exceptions.*
   a. *What were the exceptions?*
   b. *When exceptions did occur, what was done in the alternative?*

Duke Energy Indiana Response:

a. As described above, certain programs in the Base DSM Portfolio (e.g., My Home Energy Report) are designed to reach all eligible customers; therefore, it is not reasonable to assume additional participation in this program in an Incremental DSM Portfolio.

   In addition, based on recent changes in the marketplace for residential lighting, the expectation is that the customer demand for CFLs will be met through the programs offered in the base DSM portfolio so it was not reasonable to assume additional market penetration in the Incremental DSM portfolio. It should be pointed out that alternative residential lighting programs, LEDs, are included in both the Base and Incremental DSM Bundles.

b. No alternative actions are necessary. The Incremental DSM Bundles were sized and priced based on a set of technologies that did not include these two programs. The Incremental DSM bundles were introduced to the IRP models for potential selection on an equal basis to other resources.

Commission Comment – p. 10

6. *Please describe the use and interrelationships among the "System Optimizer," "Planning and Risk (PaR)," and "DSMore" in more detail (pages 126, Chapter 8).*
   a. *Are there incongruities in the modeling inputs (e.g., all 8,760 hours for the PaR versus usually significantly less than 8,760 hours for production costing models) that may affect the credibility of the results? For example, without retaining the chronology of hour (or sub-hour) use during peak periods, the credibility of demand response is questionable.*
   b. *Please provide more detail on how DSMore calculates and utilizes avoided cost in the consideration of EE.*

Duke Energy Indiana Response:

   a. While the capacity expansion model (System Optimizer) does not utilize the full 8760 hours, it does retain all peak hours each month within the subset of hours utilized for the portfolio optimization process. The demand response resources provided as inputs are then deployed by the model according to their operating characteristics to reduce demand in the subset of hours analyzed. Because all peak hours of the month are utilized in the analysis, the lack of chronology does not meaningfully reduce the credibility of the demand response resources' performance in the model results.

b. The DSMore tool has been used in Indiana for many years by the majority of the Indiana utilities. Please refer to Testimony provided by Roshena Ham in Cause 43955 – DSM3 for a detailed explanation of the DSMore tool. At a high level the tool requires the user to input specific information regarding the energy efficiency measure or program to be analyzed, as well as the program cost, avoided costs, and rate information of the utility. Using these inputs, the DSMore tool models the expected savings from a given DSM measure on an hourly basis and calculates a corresponding Avoided Cost Value on an hourly basis over the expected useful life of that measure. For the purpose of calculating Cost Effectiveness, the NPV of those hourly Avoided Costs is compared to the program costs, participant costs and other costs as recommended by the Cost Effectiveness Tests described in the California Standard Practice Manual.

   In addition, DSMore outputs an hourly savings profile for each measure that is aggregated across all of the DSM programs and this hourly savings profile is provided to the Load Forecasting and IRP group for the purpose of modeling DSM savings on an equivalent basis to other resources.

Commission Comment – p. 10

7. *Duke, like other Indiana utilities, is commended for surveying how other utilities construct there DSM bundles to treat them on a comparable basis to other resources.*
   a. *What are the lessons learned that Duke might utilize to enhance its consideration of DSM?*
   b. *To what extent, if at all, was this information from other utilities' processes incorporated into Duke's IRP?*
   c. *Does Duke intend to make any changes in its DSM bundling process in future IRPs?*

<u>Duke Energy Indiana Response:</u>

a. During the Stakeholder review and Contemporary Issues process, but too late for incorporation into the 2015 IRP modeling process, Duke Energy Indiana had discussions with other utilities about various techniques for Bundle construction that it intends to investigate for future implementation in the next IRP analysis, including modeling the Incremental DSM Bundles with more granularity related to individual Programs and potentially shortening the operating period of each Bundle (i.e. instead of assuming a 5 year minimum period for offering programs within the base or incremental bundle).

b. As mentioned above, the alternative ideas for creation and modeling of bundles were not discussed in detail until after the modeling process for the 2015 IRP was already well underway; therefore, it was not possible to fully investigate these alternative methods in time for the 2015 IRP. However, discussions have occurred with other utilities at a high level about Bundle construction that will be considered in Duke Energy Indiana's IRP process going forward.

c. Yes. As mentioned above, the most significant modification that Duke Energy Indiana intends to investigate is the concept of modeling the Incremental DSM Bundles at a higher level of granularity rather than assuming that the Incremental DSM Bundle should include all programs currently being deployed in the Base DSM Bundle. This technique will require significantly more modeling effort on the part of the IRP process but could allow for certain programs to be selected or rejected individually rather than assuming that an entire portfolio of programs must be selected.

Duke Energy Indiana will also investigate using bundles that are 3 years in duration rather than 5 years to better align with the current rules in Indiana which require approval of a DSM portfolio every 3 years and because this modeling period would better align with the actual implementation and deployment of approved DSM programs.

Commission Comment – p. 10

8. *On page 155, Duke states, "Customer behavior may not align with economic incentives further complicating efforts to accurately model EE as a supply-side resource."*
   a. *What does this sentence mean?*
   b. *How is this observation about customer behavior and economic incentives derived from the EE sensitivities?*

Duke Energy Indiana Response:

a. Experience with the deployment of DSM programs has proven that, just because the installation of a particular DSM measure makes economic sense from the customer's perspective, customers cannot always be counted on to adopt such measures. This behavior is clearly acknowledged by the fact that Market Potential Studies include an Economic Potential, which means that a particular measure makes economic sense to adopt, but these same studies also include a Market Potential (sometimes called Achievable Potential) which clearly indicates that customers will not fully participate in 100% of the measures identified in the Economic Potential.

b. This observation of customer behavior is not derived from the EE sensitivities but from real world experience with DSM programs. This observation of actual historical customer behavior was used as the basis for creating the EE sensitivities in the model.

   In modeling the EE sensitivities, we made the impact of each program larger or smaller for the same cost in PVRR terms. This was an effort to model a higher or lower than expected adoption rate by customers. Because the model chose the EE bundles economically, this sensitivity lead to an increase or decrease in bundle selection due to the increased or decreased cost effectiveness of each bundle due to the variation in assumed adoption rate.

C. Avoided Costs

Commission Comment – p. 11

Without violating trade secrets and proprietary concerns, additional clarity would be helpful to detail how avoided costs were calculated and how the models used avoided costs in the IRP.

a. If the avoided cost of the potential combined cycle affected the avoided costs, how did it change the cost effectiveness of DSM, demand response, and other resources?
b. In general terms, how does Duke integrate avoided cost calculations in all its scenarios?

Duke Energy Indiana Response:

a. As stated previously, DSM programs were not screened out prior to submission to the modeling process based on cost effectiveness so any changes in the expected Avoided Costs from the IRP model were not applied to the DSM bundles prior to submitting them to the model for comparison to other resources.

The models used for IRP analysis do not use avoided cost in the traditional sense as an input for the selection of resources; rather, avoided cost is a model output based on a specific scenario/portfolio combination. The models iterate though multiple combinations and timing of resource additions and retirements, refining them until the lowest cost combination is determined which meets the reserve margin requirement and customer demand and energy needs.

With regard to the addition of the combined cycle plant, the associated increase in PVRR of the portfolio would generally serve to make DSM, demand response and other resources more cost effective and more likely to be selected by the model for additional resource needs.

b. As described in part a. of this response, explicit avoided cost calculations (in \$/MWh) are not utilized as inputs to the planning models for resource screening or selection. The iterative analysis done by the planning models provides a similar effect to using avoided costs to screen and select resources but using a significantly different methodology.

D. Weather Normalization

Commission Comment – p. 11

a. Could Duke please explain the weather normalization process?
b. Is our reading of the IRP correct that there are no longer any details on how the weather normalization is done in the IRP? The math would also be helpful.

Duke Energy Indiana Response:

a. Normal weather is computed based on an arithmetic mean of the Heating Degree Days ("HDD's") and Cooling Degree Days ("CDD's") for the ten prior calendar years to when the forecast was done, (*i.e.*, 2005-2014). This calculation is performed on a monthly basis to determine the weather normal HDD's and CDD's for sales, and on a daily basis to determine the average daily temperature during the summer and winter peaks. Duke Energy cares greatly about properly predicting this weather series through its weather normalization process; and will subsequently be transitioning to a thirty year period for calculating normal weather for future IRP submissions.

b. Yes, it is correct that in the 2013 Duke Energy Indiana IRP there was a small section that described the weather normalization process (p. 28) that was omitted in 2015. While the weather normalization details were not included in the 2015 IRP, the process followed is described above.

E. Derivation of Peak Demand Estimates

Commission Comment – pp. 11-12

1. *It is not clear how Duke calculated the system peak demand. The peak load methodology seems to have changed from separate summer and winter econometric models to some kind of hybrid econometric/end-use approach. However, the write-up does not have enough details to make it clear what is being done. The weighting of the month's discussion is particularly confusing. The peak models used to be estimated on days that could produce a peak: 90 degrees and above for summer and below a certain temperature for winter. However, now, Duke's IRP just states that it is a "predetermined threshold" without specifying what that temperature is.*
    a. *Why?*
    b. *What threshold was used?*
    c. *Would Duke please provide additional information to explain how it developed its peak demand? Again, a mathematical example would be helpful.*

<u>Duke Energy Indiana Response:</u>

a. The change in peak estimation was made for two reasons: first was to employ the statistically adjusted end-use ("SAE" or "end-use") data to better link the peak methodology with the SAE approach for estimation of MWH sales forecasts. Secondly, the old method also carried an implicit assumption of a constant load factor, which was problematic after a year of high energy sales combined with very weak summer peak results (i.e., 2014, in which a particularly cold winter resulted in substantial accumulated energy sales coincident with a mild summer and summer peak). By incorporating changing energy and peak predictions through monthly data, the new method allows load factor to change throughout the sample, while also using more data points to estimate the relationship between weather and peak sales.

b. The peak day in July—which is reported as the peak for the year—depends on an *<u>average</u>* daily temperature of approximately 85 degrees Fahrenheit.

c. The new model for retail peak demand is estimated from monthly data on retail peak. Independent variables in this model are a measure of heating end uses, a measure of cooling end uses, and a measure of base load end uses (i.e., water heating, cooking, lighting, etc.) The measures of heating and cooling end uses are built from appropriate SAE data for both residential- and commercial-class customers. The measure of base load end uses combines some of residential and commercial sales with Industrial, OPA, and streetlight-class sales. After this estimation, anticipated loads for contracted wholesale relationships can be added to produce a final system peak. To display this with a mathematical example would be difficult and further confusing, so if the explanation above leads to further clarifying questions, we welcome additional discussion regarding this issue.

Commission Comment – p. 12

2. *Consistent with EIA's forecasts, Duke's forecast on page 39 shows peak demand growing more quickly than the rate of energy sales.*
   a. *Does Duke anticipate a reexamination of the economic warrant for increased demand response, the value of peak demand reductions due to EE, and incentives for increased customer-owned generation to reduce Duke's peak demand?*
   b. *Because Duke may add a combined cycle (CC) in the relatively near term, the cost of alternative resource solutions seems certain to increase in cost-effectiveness over the 20-year planning horizon. Does Duke agree?*

Duke Energy Indiana Response:

a. Duke Energy Indiana considers demand response, peak demand reductions due to EE and customer owned generation as viable methods to reduce Duke Energy Indiana's peak demand and all of these options are already considered as part of the IRP modeling process.

b. The potential addition of a combined cycle plant in the near term would potentially serve to make DSM, demand response and other alternative resource solutions relatively more cost effective due to the increase in system PVRR from the additional capital costs. This would generally increase the likelihood that the planning models would select additional alternative resources in the later years of the planning period.

Commission Comment – pp. 12-13

3. *The high and low scenarios were developed using statistical bands at the 95% confidence level. This represents a change from the methodology used in the 2013 IRP in which the first five years were based on high and low economics with statistical bands applied for the remainder of the forecast period.*
   a. *Why did this change occur?*
   b. *Intuitively, Duke must have concluded the risk bands better assessed risk. However, it seems the previous approach is arguably better than purely statistical bands. Would Duke please provide its rationale and perspective?*

Duke Energy Indiana Response:

a. In adopting the ITRON modeling tool for the new end-use models, this statistical calculation was made readily available to determine the high and low bands. At times, Duke Energy Indiana has used privately-prepared forecasts adjusting the macroeconomic variables to determine a high and low case, however much judgment was needed to produce these cases. Often these scenarios are the issuer's guess as to possible future economic trends, and how they may vary from their base case, but there is little guidance about the probability of the scenario. Additionally, the scenarios may result in discrepancies in their ordering, for example a "low" scenario may demonstrate weakness in the short-term, however as the growth reverts to a “normal”, the same scenario can show a higher long-term equilibrium level of activity. Therefore, ranking the scenarios as “high” and “low” would depend upon articulating a time frame within the planning period in which this ranking is to be maintained. Because of the judgment calls and the availability of providing a statistically high and low within the modeling tool, Duke Energy Indiana chose this newer method.

b. Please see the response to subpart (a) above.

F. Changes in Load Forecasting Methodology

Commission Comment – p.13
1.

a. Because Duke’s projections of low load growth are not likely to be a significant driver of resource decisions, would it have been useful for Duke to have a broader risk band on load forecasting? In other words, would a relatively high and low load growth scenario provide additional information about the potential ramifications of over- or under-estimating load growth?
b. Is our understanding correct that the high and low range of the load forecast was determined by applying the standard error of the FERC-class estimation models using a 95% confidence interval? (page 39)
c. Why did the change from the past practice of having forecast ranges based in part on macroeconomic drivers occur?
d. Does the use of statistical bands assume the macroeconomic forecast is correct and all load forecast error is entirely statistical error? In other words, could any errors be driven by inaccurate macroeconomic variable/driver forecasts?
e. Is there any concern that reliance on statistical bands might obscure problems in the model specifications which, if they occur, would not be corrected?

<u>Duke Energy Indiana Response:</u>

a. Yes, Duke Energy Indiana will be exploring such high and low load growth scenarios or sensitivities when making resource decisions and in its next IRP.

b. This understanding is correct (see response to “Derivation of Peak Demand Estimates” #3 above).

c. Please see response to “Derivation of Peak Demand Estimates” #3 above.

d. Yes, the statistical approach is subject to both statistical error as well as input “errors” covering inaccurate macroeconomic variables.

e. Duke Energy Indiana shares this concern. To address this, our internal procedures involve consideration of many different models and balancing across a variety of model statistics, as well as cross-validations to prevent spurious relationships from driving model conclusions.

Commission Comment – pp. 13-14

2. *The residential forecast. Duke made several changes to the load forecast methodology [beginning on page 30 of the IRP]*
   a. *Residential load is modeled with two equations – residential customers and use per customer (UPC) – and the results are then multiplied together to get the residential sales forecast. Residential customers now appears to be an explanatory variable in the UPC model itself. Is this accurate?*
   b. *Does the residential customer model no longer include real per capita income as a driver?*
   c. *The UPC model also includes a driver called "Residential Appliance Intensity." Is this what Duke refers to on page 31 of the IRP as the "combined impact of numerous other determinants tracked by the Energy Information Administration (EIA) that include the saturation and efficiency of air conditions, electric space heating, other appliances, the efficiency of those appliances?" It is not completely clear how this information was included in the load forecast. Would Duke please provide a discussion about the rationale for these changes?*

<u>Duke Energy Indiana Response:</u>

a. Yes, it is accurate that residential customers are used as an explanatory variable in the Usage-Per-Customer model.

b. Indiana population in households is the current economic driver in the residential customer model. Real per capita income is not an economic driver in the current model.

c. Yes. The incorporation of Utility Energy Efficiency (UEE) and naturally occurring efficiencies as provided by EIA on an annual basis was discussed earlier under the "Construction, Evaluating, and Integrating DSM bundles" To incorporate the EIA-provided naturally occurring efficiencies, ITRON provides an input file which is informed by EIA's Annual Energy update, which identifies the rate at which efficiencies are expected to be adopted. This efficiency adoption is used in the end use models to recognize the expected future reductions to sales and load.

Commission Comment – p. 14

3. *As part of continual improvements envisioned by the IRP rule and given the increased deployment of advanced metering infrastructure (AMI) and smart grid, Duke's thoughts on how the information from these new systems would be integrated into various aspects of the IRP would be appreciated.*
   a. *How does Duke anticipate utilizing the information to enhance load forecasts? For example, will this be used to enhance load research?*
   b. *How does Duke anticipate using the information from AMI, in particular for consideration of EE, demand response, and customer-owned resources?*
   c. *What enhancements, if any, does Duke anticipate making to its future residential load forecasts?*

Duke Energy Indiana Response:

a. Yes, it will. Load research currently studies a sample of the universe of data to inform load forecasting of load shapes by customer class. With a full build out of the AMI meters, forecasting would be able to review load shapes from all customers, enabling better shapes, as well as the ability to look at subsets of customer data to determine if different customers react differently and should therefore be modeled separately. Usage of the data to enhance estimates of load shapes will produce peak estimates that are subject to narrower confidence intervals.

b. Duke Energy Indiana expects that information from AMI will facilitate the deployment of certain types of future DSM programs that are enabled by real-time knowledge of customer usage and, as that technology develops over time, those programs will be included in the portfolio of DSM to be modeled in the IRP.

c. Our internal procedures involve consideration of many different models and balancing across a variety of model statistics, as well as cross-validations to prevent spurious relationships from driving model conclusions. Specific to the Residential forecast, updated EIA data on efficiency and penetration of technologies will lead to constant improvement of forecasts.

Commission Comment – pp. 14-15

4. *The industrial forecast has changed to include "billing day." In previous forecasts, "industrial sales" was the lone dependent variable.*
   a. *What is the rationale for the change?*
   b. *Why are "Regional manufacturing GDP," "Electric price relative to other fuels," and weather no longer drivers in the model? (page 31)*
   c. *Is any significant part of the production process, for any industrial customer, sensitive to weather changes?*

Duke Energy Indiana Response:

a. The model was estimated on a per-billing-day basis so as to tighten parameter estimates regarding the impact of economic drivers on sales. Confidence intervals around the model coefficients improved substantially upon making this change.

b. On page 31 of the Indiana IRP, we mention that the *primary* drivers to the industrial forecast are industrial production, employment, and the impact of electricity prices. "Regional Manufacturing GDP" was replaced by a measure of output called the Industrial Production Index. Cross-validation of randomly removed sample observations showed that a model with these predictors forecast within sample sales with less error. Therefore, an economic indicator (replacing regional manufacturing GDP), electric price and weather all drive the industrial sales model.

c. When we examine how changes in weather affect changes in electric sales, the industrial class of customers is not as sensitive to weather changes as other classes of customers.

Commission Comment – p. 15

5. *Given the increasing importance of the industrial class to the load forecast to the IRP, Duke's perspective would be appreciated.*
   a. *What steps does Duke intend to consider to improve the insights and credibility of the industrial forecast?*
   b. *Has Duke considered having its industrial representatives and other experts getting more detailed information?*

Duke Energy Indiana Response:

a. Duke Energy Indiana continually looks to improve upon its load forecasting practices. With regard to the industrial class, we try to gain insight into the health of this class, and to specific customers through discussion with our large account representatives and listening to some of the customers' quarterly earnings calls to gain insight as to their operational expectations.

b. Yes – see above.

Commission Comment – p. 15

6. *The commercial forecast now appears to be hybrid end-use model instead of the econometric model Duke used for many years. This may be appropriate, but we would like to have Duke's rationale for the changes.*
   a. *By way of examples, why is commercial employment no longer a driver?*
   b. *Saturations and efficiencies are scaled by square footage for different commercial activity sectors in the model; however, nothing is listed in the model equation. Would Duke please explain?*

Duke Energy Indiana Response:

a. For this particular model, cross-validation within sample showed that a model based on non-manufacturing GDP more accurately forecast sales than one based on commercial employment. Employment is typically seen as a trailing economic indicator when compared with output-based measures, so this result was unsurprising.

b. Surveys of commercial use categories (examples are "Lodging", "Large Office", "Warehouse"…) are combined with EIA data on end-use per square foot to produce an aggregate estimate of the amount of each end-use within the DEI service territory. These historical estimates can be scaled through future years using the annual change-numbers in end-use penetration and efficiency from the EIA.

Commission Comment – p. 15

7. *For future IRPs, recognizing that the commercial class is very diverse, what steps is Duke considering to improve the explanatory value of the commercial forecast. For example:*
   a. *Has Duke considered grouping the commercial class into more homogeneous subgroups to improve the insights and credibility of the commercial forecasts?*

b. Especially with the potential for higher avoided costs, would greater granularity in the information about the various types of customers provide information to better target demand response, EE, and customer-owned resources?

<u>Duke Energy Indiana Response:</u>

a. Duke Energy Indiana is not actively considering this and not aware of any major utilities who are having significant success through this type of endeavor. It is Duke Energy Indiana's opinion that the end-use methodology already gives substantial measurement of heterogeneous customer types. The Company would, however, welcome Commission suggestions in this regard.

b. While greater granularity would help in many planning facets, from a forecasting perspective greater granularity is typically achieved through employing lower-level data (which are subject to additional measurement error) and multiplying the number of parameter estimates which are then re-added. Duke Energy Indiana looks at appropriate levels to forecast in order to balance these risks and rewards.

Commission Comment –p. 16

8. *Regarding agricultural use, stakeholders expressed strong opposition to Duke's use of North Carolina examples (e.g., poultry waste being used to produce fuel on page 97). Stakeholders suggested that the IRP's credibility would be enhanced if Indiana examples were used.*
   a. Has Duke considered using Indiana-specific research to assess the potential?
   b. What Indiana data sources might be used to provide the Indiana-specific data?

<u>Duke Energy Indiana Response:</u>

a. The use of North Carolina based examples of agricultural power generation projects was due to the ready availability of known and verifiable data related to these projects because of a specific allocation for these types of projects within the North Carolina Renewable Portfolio Standard. While Indiana-specific projects likely differ than the examples studied, it is unlikely that these projects would screen favorably in comparison to other renewable resources such as wind or solar. We are open to utilizing Indiana-based projects for the screening evaluation if valid and verifiable data can be obtained for analysis.

b. Potential data sources for Indiana-specific projects would be current and historical data from existing projects operating within the state. Identification of these candidate projects for evaluation is an area where ongoing stakeholder engagement would be of value to Duke Energy Indiana.

Commission Comment – p. 16

9. *Governmental (OPA) model. As with the industrial forecast, the OPA forecast has changed to "sales per billing day." In the past, OPA sales alone was used as the dependent variable.*
   a. Why did this change occur?
   b. Does Duke plan to make any enhancements to the OPA?

Duke Energy Indiana Response:

a. Duke Energy Indiana modified the model for MWh sales to OPA-class customers because recent trends in sales and government employment caused problems in the fit of the model once the most recent data were added. The predictors in this model—both weather-related and economic-related—were recalculated to fit the billing schedule, which can often result in individual months differing by 1-2 days in length from their calendar lengths.

b. Duke Energy Indiana maintains a consistent program of re-evaluating the forecasting models as part of its routine forecast cycle. At this point, no known changes are being proposed, but as we evaluate and develop more current forecasts every year, further improvements may be identified and incorporated.

Commission Comment – p. 16

10. With the substantial change in the resource mix over the next 30 years, there is an expectation that Indiana utilities will give increased consideration to regional developments.
   a. How does Duke anticipate working with the MISO on enhancements to its load forecasts and long-term resource planning in an effort to improve the credibility and, hopefully, have a positive effect on resource adequacy requirements and provide other benefits?

Duke Energy Indiana Response:

Over the past three years, MISO and OMS (Organization of MISO States) have conducted a resource adequacy survey of market participants in order to develop a MISO footprint-wide view of aggregate load forecasts, generation resource retirement plans and future construction, wholesale transactions and other considerations related to resource adequacy. This survey is a forward looking 10 year view which will assist MISO in identifying potential capacity shortfalls on a zonal or footprint-wide basis. Duke Energy Indiana will continue to participate in this survey and other resource adequacy initiatives to ensure adequate capacity resources are available to serve Duke Energy Indiana's native load retail and wholesale obligations. Our continued participation in these initiatives will also assist MISO and the IURC in ensuring resource adequacy for all of MISO Zone 6 (Indiana).

III. Duke Energy Indiana's responsive comments to stakeholder comments

Stakeholder comments were received from the Citizens Action Coalition of Indiana, Earthjustice, Indiana Distributed Energy Alliance, Michael A. Mullett, Sierra Club, and Valley Watch (collectively, "Commenters").

Modeling of Renewables

Contrary to Commenters' concern, Duke Energy Indiana did not assume that solar costs would remain unchanged throughout the 20-year planning period. The rapid decline in solar costs noted in the stakeholder comments has begun to slow and is generally projected to level off in future years. To model this slowing decline, we held the price constant in real terms for several years, which equals a 2.5% decrease per year in nominal terms based on the 2.5% general inflation rate assumed in our planning models. After the period where solar cost was held constant in real terms, it was allowed to inflate at 2.5% similar to the cost of other mature technologies.

The capacity factor applied to wind in the planning models was actually significantly higher than our historical capacity factors for the Benton County facility. The first 300 MW was modeled at a 44% capacity factor, reflecting the potential availability of certain optimal siting locations. The remaining wind resources were modeled at a 30% capacity factor which is in line with historical performance at the Benton County facility and other well-sited wind farms in Indiana.
The extension of renewable energy tax credits was not certain or approved as of the date of filling the IRP, let alone during the time period when modeling occurred. Once the extension was finalized, it was and will continue to be incorporated in planning model runs for internal planning purposes, as well as modeling to support any future regulatory filings.

Modeling of Existing Units

The stakeholder contention that Gallagher Units 2 and 4 will incur fixed and variable costs exceeding their market revenues is flawed in that the stakeholder analysis only takes into account projected energy market revenues. The units will also generate significant capacity market revenues (or avoidance of significant replacement capacity costs) during their remaining years of operation. Duke Energy Indiana does not agree that unit costs exceed the energy and capacity revenues.

In addition, the results of the MISO capacity auction for planning year 2016/2017 generated a capacity value more than 5x higher than that assumed in prior analyses. This indicates that Gallagher’s capacity and energy revenues will exceed the units’ costs by an even larger amount than the Company previously anticipated. Capacity value is a significant revenue stream in the analysis of any generating resource and especially so for conventional, dispatchable resources and thus, should always be considered in evaluating the economics of a plant’s continued operation or retirement.

The stakeholder concern about a constraint placed on System Optimizer was previously addressed in Duke Energy Indiana’s response to questions 1 and 2 of the Risk Analysis section of the Duke Energy Indiana Reply to 2015 IRP Comments. Duke Energy Indiana had intended to make clear in the stakeholder meetings and the IRP document that the substitution of combined cycle capacity in 2020 for combustion turbine capacity was by design and done to examine market purchase mitigation, CO_2 reduction and improved fuel diversity. To accomplish this in the applicable portfolios (denoted by “with additional CC” in the portfolio title), Duke Energy Indiana placed a ‘MinAnnualUnits’ constraint of ‘1’ in 2020 for a 448MW combined cycle unit, as this would be how to create the intended portfolio when all other optimization parameters are unconstrained.

Assumed Reserve Margin

MISO establishes its planning reserve margin requirements (PRMR) annually for the MISO Capacity Planning Year which runs from June 1 through the following May 31. For the 2015 IRP, we utilized the MISO PRMR of 7.1% applicable to Planning Year '15/'16. The MISO PRMR is stated on a UCAP basis. To convert this to an ICAP basis (which is used by Duke Energy Indiana's resource planning models), the UCAP PRMR is utilized in the following formula as stated in footnote 8 on page 26 of the IRP: RM_{ICAP} = Coincidence Factor * [(PRM_{UCAP}+1)/(1- DEI average $XEFOR_d$)]-1 = 98.74% * [(7.1% + 1)/(1 – 6.94%)] – 1 = 13.6% This calculation is explained on pages 26-27 of the IRP. The following additional details may be helpful:

1. The coincidence factor is determined by the ratio of the Duke Energy Indiana non-coincident peak demand to Duke Energy Indiana's MISO-coincident peak demand (Duke Energy Indiana peak at time of MISO peak).

2. The MISO calculated Duke Energy Indiana average $XEFOR_d$ for planning year '15/'16 is 7.98% which would have resulted in a 14.9% RM_{ICAP}. Because this Duke Energy Indiana average $XEFOR_d$ changes annually and can be significantly influenced by performance anomalies at individual units, Duke Energy Indiana believes it is prudent to make adjustments to reflect the typical long term performance of generating units. This adjustment resulted in the 6.94% $XEFOR_d$ used to calculate the 13.6% RM_{ICAP}.

Load Forecast

In terms of sales, many macro-economic indicators are forecast to continue a robust recovery from the recession of 2007-2009. The forecasting models, while incorporating sales reducing activities such as energy efficiencies, are still very reliant on third party economic forecasts. By review of the data in table 3-B, growth rates from 2012 to 2015 have been at or above 1%. That strength is expected to continue for a short timeframe (2015-2020 compounded average growth rate ~1.0%), and then revert to a slower more "normal" growth rate of around 0.5% as the economy closes the gap between potential GDP and current GDP.

Regarding the peak, there are many similarities to the sales trends described above. However, there have been a string of summers where the weather at time of peak was weaker than normal, often implying substantial weather adjustments. We assume a normal or average weather for purposes of forecasting peak (as is done for sales), so much of the near term growth in the forecast is the effect of returning to normal weather. Again, after the short term growth, the longer term trend growth rate is close to 0.5%, very similar to the anticipated sales growth rates.

Energy Efficiency:

1. As explained in response the IURC Draft Report Comments, Duke Energy Indiana did not "pre-screen" for cost effectiveness
   a. As stated in the IRP, the first Base DSM Bundle (2015-19) was based on a combination of the 2015 approved portfolio, the 2016-18 proposed portfolio and an expectation that the EE programs in 2019 would provide the same overall EE

impacts as 2018. Because these underlying portfolios, 2015 and 2016-18, were required to be cost-effective per the IRP rules, this proxy portfolio was evaluated for cost effectiveness but this was not used as a means to reduce the ability of the IRP to select EE programs. This first Base DSM Bundle was only a starting point for the creation of a set of EE bundles to be evaluated by the IRP.

b. There was no pre-screening performed to eliminate programs. In fact, no cost-effectiveness testing was performed on any of the other nine bundles prior to analyzing the bundles in the IRP process.

2. Duke Energy Indiana did not "hardwire" only the 2016-18 DSM portfolio

   a. In order to create a starting point for the IRP analysis, Duke Energy Indiana used the currently approved 2015 DSM portfolio and the proposed 2016-18 DSM portfolio as a proxy for a reasonable portfolio that was proven to be accepted in the marketplace and was feasible to implement. However, this proxy DSM portfolio was only one out of multiple bundles of EE that the IRP process was allowed to select in the analytical process. It was not hardwired into the plan. In addition, the use of a portfolio that was based on the 2016-18 DSM portfolio had no impact on limiting the amount of EE that was ultimately chosen by the IRP, because other incremental DSM bundles were also available for selection by the IRP process.

   b. By letting the IRP model determine if it would select the existing portfolio of proven and proposed programs, Duke Energy Indiana is able to confirm that the portfolio is cost-effective within the context of the IRP. Then, once that portfolio is selected by the IRP process, as a starting point, it makes sense to provide additional similar proposed bundles of EE, not specific measures. These were created and provided as additional EE options for the IRP to choose, or not.

3. Duke Energy Indiana does not agree that DSM should be modeled from the Technical Potential down but rather from the current programs up.

   a. As explained above, Duke Energy Indiana did not constrain the EE bundles or cap the potential for the IRP process to select them.

   b. The Incremental DSM bundles allowed the opportunity for the IRP process to choose additional EE impacts if economically justified.

   c. While it may be desirable, in the opinion of Commenters, to start with the overall Technical Potential, it is not relevant to the IRP process because the IRP was given the opportunity, through the Incremental DSM Bundles, to choose additional EE over and above the Base DSM Bundles and it did not choose more EE in most scenarios.

IV. Conclusion

Duke Energy Indiana's IRP process, assumptions, and methodologies were reasonable, especially in light of the fact that the IRP is a planning document meant to provide insights into the future rather than acting as decisional document. Duke Energy Indiana appreciates the opportunity to address comments provided by Dr. Borum and stakeholders to further the understanding of the Company's 2015 IRP.

CERTIFICATE OF SERVICE

The undersigned hereby certifies that a copy of the foregoing reply comments were mailed electronically this 20th day of June, 2016, to the following:

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Energy Efficiency Program Costs, Program Size, and Market Penetration

By

Richard Stevie[1]

1. Introduction

Utility sponsored[2] energy efficiency programs have been implemented in varying degrees for over 20 years across numerous customer segments. Demand response programs, however, have been around for decades beginning with interruptible or off-peak type rate offerings that existed in the 1940's and expanded to include cycling of end-use equipment and more sophisticated dynamic pricing structures.

Besides the fact that the implementation of energy efficiency and demand response programs involves significant complexity in marketing, communication, and cost-effectiveness analysis, information on the costs to implement are very difficult to unravel due to the multi-year life of measures in the portfolio of programs. The major source of historical data on costs and impacts is the Energy Information Administration (EIA) which is part of the Department of Energy. Using Form 861, the EIA has been collecting cost and load impact data, among other items, for energy efficiency and demand response efforts for all utility service areas in the United States since 1990.

This paper focuses only on the costs and load impacts associated with implementation of energy efficiency (EE) programs. Investigation of demand response costs is reserved for future

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[2] For purposes here, utility sponsored includes programs implemented by third parties, including third party administration efforts.

study. The energy efficiency cost and impact information available on the EIA web site includes current year direct program spending, indirect spending (e.g., administrative costs not directly associated with a program), current year energy efficiency MWH and MW impacts, as well as cumulative MWH and MW impacts for each utility service area for the period over which the EIA has been collecting the data[3]. However, the cost and impact data represent totals for the portfolio of energy efficiency programs. Values at the individual program level are not available from the EIA data. For the year 2012, the EIA data on direct plus incentive expenditures for the 50 states plus District of Columbia totaled $4.4 billion. Through this level of spending, the current year retail energy impacts were 21,478,470 MWH which results in a first year[4] cost of $0.205 per kWh. Furthermore, the cumulative[5] EE load impacts reported total 138,524,613 MWH. These on-going cumulative impacts represent the sum of the historical impacts achieved by the programs as reported to EIA.

The issue here is the cost. The value of $.205/kWh represents the total program spending per kWh in one year to gain a stream of kWh savings over the life of the installed measures. If one knew the life of the measures being implemented as well as the relevant discount rate, one could calculate a levelized cost in order to compute a levelized cost per kWh, a commonly used metric for comparing costs across supply-side and demand-side options. For example, for the $0.205/KWh first year costs cited above, if the discount rate were 8% and the measure life averaged to five years, the levelized cost per kWh converts to 5.1 cents/kWh.

To benchmark current costs and project future costs, there are three issues with this analysis. One, the discount rate and relevant measure life are unknown. Changes to either or both

[3] EIA stated in the past that the cumulative impacts should represent total impacts since 1992. However, this may change in the future as the EIA has indicated it wants to incorporate measure life into these load impact estimates.
[4] First year cost is defined as the total program spending divided by the load impacts achieved in the first year of program implementation.
[5] For clarity, cumulative load impacts, defined as Annual by the EIA, represents the sum of the incremental load impacts.

significantly impact the resulting cost estimate. Two, the number represents an average. The cost for a specific program can vary substantially from this average estimate. And three, the level of historical penetration of EE in any one utility service area can be quite different from the average. In some utility service areas, the cumulative impacts can be large, exceeding 10% of retail sales. In other service areas, the cumulative impacts have been minor, less than 1%. Using an average cost estimate from the EIA data ignores all of the utility specific details that could affect cost. This raises a critical question. As the cumulative market penetration of EE rises, does the cost to achieve further incremental energy efficiency impacts rise or fall or stay the same? One typically expects the marketing cost to attract the early adopters to be somewhat elevated due to the cost of the startup. Then, as the program size expands, there can be some marketing economies of scale driving down the unit cost. But, as the cumulative market penetration rises, the marketing cost per unit to attract additional interest could be expected to rise.

This paper takes a new look at the EIA data in an effort to glean how the level of market penetration could affect unit implementation costs. By examining how the cost of implementing EE programs changes across the states, one can begin to gain insight on the incremental cost of EE through analysis of areas where the market penetration is low versus where it is high.

The following sections provide:

- Brief review of past studies of energy efficiency that reported implementation costs,
- Discussion of the modeling approach,
- Review of issues related to the use of the EIA data,
- Presentation of the modeling results, and
- Summary of the results along with comments on applicability and implications for future research.

2. Past Studies

A large volume of literature has been devoted to studies on energy efficiency and the costs associated with program implementation. Study categories include those that summarize costs and impacts based on other reports (meta-studies) and those that conduct a bottom-up analysis of end-use efficiency. The studies provide estimates of the market potential and the levelized cost to implement energy efficiency. The levelized cost estimates represent an average expected cost for implementing a program or measure or portfolio of programs.

Generally, the focus of these studies has been on market size and cost in a macro perspective, though a few examine the costs associated with individual programs or measures. As the spending on energy efficiency escalates due to energy efficiency portfolio standards (EERS) or potentially new EPA rules[6] requiring energy efficiency impacts of 1.5% of retail sales each year, the cost-effectiveness of energy efficiency programs and measures could change as the market penetration of energy efficiency increases. The research to-date has not provided any insight or guidance on this issue.

The American Council for an Energy Efficient Economy (ACEEE) has produced numerous reports, studies, and meta-studies on energy efficiency market size and cost-effectiveness[7]. The ACEEE reports tend to focus on the estimates of program costs per kWh. In addition to estimating the size of the potential, ACEEE compiled information on unit cost estimates from reports by state utility commissions as well as individual utility reports. While these reports provide a significant

[6] See Section 111d on energy efficiency in the U.S. EPA's GHG Abatement Measures in Docket ID No. EPA-HQ-OAR-2013-0602.

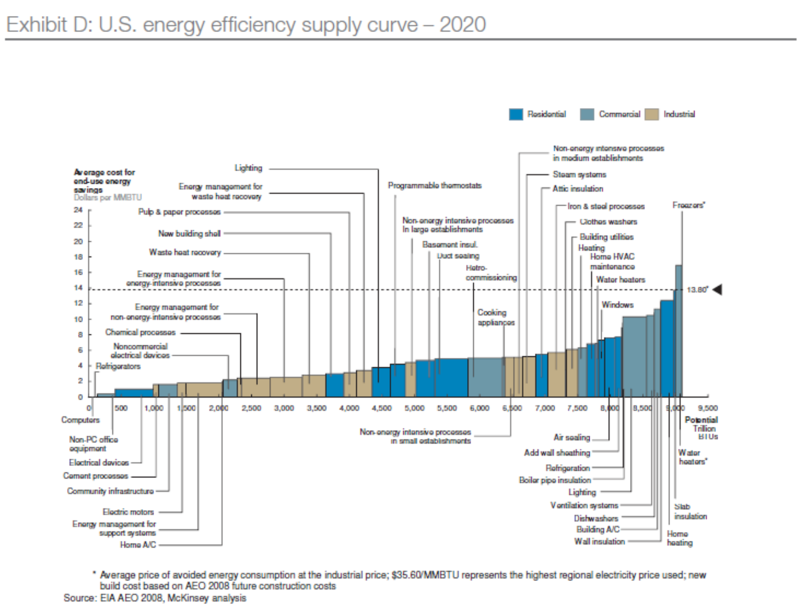
[7] See Chittum (2011), Eldridge et. al. (2010), Elliott et. al. (2007), Friedrich et.al. (2009), Kushler (2004), Laitner et. al. (2012), Nadel and Herndon (2014), Neubauer et. al. (2009), Neubauer and Neal (2012), Neubauer and Elliott et. al. (2009), Shipley and Elliott (2006), and Takahashi and Nichols (2008).

volume of cost related information, none of the reports investigate or estimate how the unit costs might vary as the cumulative market penetration increases.

The Electric Power Research Institute investigated the market potential for EE in two relatively recent reports[8]. These reports also examined program cost-effectiveness as well as market size. But again, neither of these reports provided insight on how the unit costs might vary as the cumulative market penetration increases.

McKinsey & Company also produced a report[9] on EE potential in 2009. In addition to providing estimates of market potential, McKinsey presented a graphical view of the EE supply curve as shown in Figure 1. The chart cleverly combines energy efficiency market potential for each end-use with the average annualized cost to implement the efficiency improvement on a dollars per MMBTU basis. The width of the bars represents the market potential while the height depicts the unit costs.

Figure 1



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[8] See Electric Power Research Institute (2014) and Rohrmund et. al. (2008).

[9] See McKinsey & Company (2007) and (2009). See the Executive Summary page 6.

While the chart demonstrates that unit costs will increase as the market potential for the portfolio of programs is achieved, the report does not provide guidance on how the costs vary as the cumulative market penetration changes for each measure.

Several other studies[10] presented estimates of the market potential and/or the unit costs for energy efficiency. However, these studies also do not examine how the unit costs may change as the cumulative market penetration increases.

Four additional studies investigated the presence of economies of scale in the implementation of energy efficiency programs[11]. Two of these[12] essentially relied on the same research results. Both studies reported declines in the unit costs with increases in incremental first year energy saving (as measured by percent of retail sales). However, neither study considered the impact of cumulative market penetration in unit costs. A very recent report[13] published by Lawrence-Berkeley National Laboratory that found a slight decline in the levelized unit cost curve as participation increases for a specific program, appliance recycling. However, the report indicates that this relationship was not statistically significant for any other program studied. While the study claims that cost efficiency exists for this one program, the report does not indicate whether the unit cost estimates could have been influenced by the size of the different markets or whether or not unit costs decline as cumulative market penetration increases.

The fourth study[14] is the first identified to pose the question as to the existence of increasing returns to scale with diminishing marginal returns. In other words, the researchers contend that the unit costs of implementing energy efficiency programs will decline with increases

[10] See Barbose et. al. (2009), Brown et. al. (2010), Cappers and Goldman (2009), Chandler and Brown (2009), Energy Center of Wisconsin (2009), Forefront Economics et. al. (2012), Forefront Economics and H. Gil Peach and Associates (2012), GDS Associates (2006), GDS Associates (2007), Itron, Inc. et. al. (2006), La Capra Associates, Inc. et. al. (2006), McKinsey & Company (2007), Nadel and Herndon (2014), Midwest Energy Alliance (2006), Western Governors' Association (2006), Wilson (2009), and U.S. Department of Energy (2007).
[11] See Billingsley et. al. (2014), Hurley et. al. (2008), Plunkett et. al. (2012), and Takahashi and Nichols (2008).
[12] See reference number Hurley et. al. (2008) and Takahashi and Nichols (2008).
[13] See Billingsley et. al. (2014).
[14] See Plunkett et. al. (2012).

in scale (measured by percent of retail sales), but at some point unit costs for the first year savings will increase due to diminishing returns. The researchers arrive at this conclusion based on an econometric analysis that suffers from over-fitting of the data and an application that leads to a bias in the coefficients[15]. Further, this research only examined unit costs associated with incremental first year savings, not cumulative market penetration. While one of the first studies, if not the first, to pose the right questions, the research falls short of providing any enlightenment on the impact of cumulative market penetration on unit costs.

Finally, one study by Cicchetti[16] conducted extensive analysis on the unit cost of energy efficiency. Using the data compiled by the EIA, Cicchetti computed costs on a first year as well as a levelized basis. Cicchetti conducted an extensive analysis of the costs, however, again there is no insight provided on the impact of market penetration on costs.

In summary, this review of past studies on the costs of energy efficiency reveals that a significant void exists in our understanding of how the implementation costs of energy efficiency are affected by the level of market penetration. Assume for a moment that the cost-effective economic market potential for a utility service area is 20% of retail sales and that the levelized unit cost is assumed to be 5 cents/kWh. Then, the unanswered question is whether or not the 5 cents/kWh cost remains constant as the achieved percent of market potential rises from 10% (of the 20% economic potential) to 50% to 100% (see Figure 2). Can one reasonably assume that the cost to acquire the first 10% of market potential is the same as the cost to acquire the last 10% percent of the market? Or, does the unit cost become higher or lower as the portion of the market potential achieved increases?

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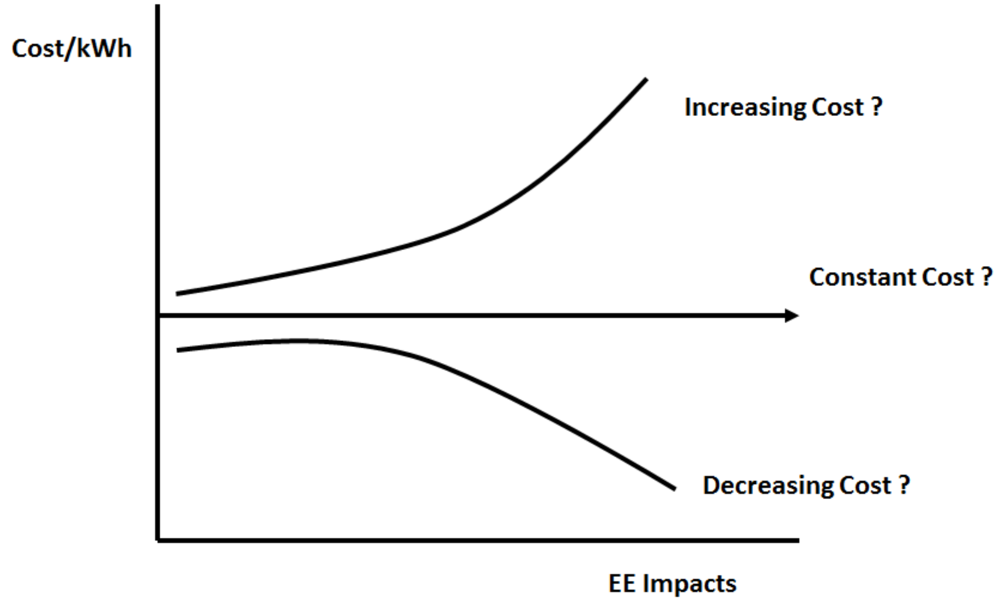
[15] The researchers apparently tried multiple mathematical forms until they found the one with the best fit. In addition, besides using a model with specification issues, the researchers boosted the fit of the model by dropping the intercept term, an arbitrary approach that produces biases in coefficients.
[16] See Cicchetti (2009).

Figure 2



The following sections of this study will provide an initial attempt to shed light on this issue.

3. General Model Discussion

The cost of energy efficiency implementation depends significantly on the type of program or measure being implemented. The typical cost components include project administration, marketing, financial incentives paid to customers or marketing channels, and evaluation, measurement and verification. Indirect / overhead costs are not included in this list. Inclusion of indirect items could add another 30% to the total program costs[17].

The key drivers of annual cost are the number of measures or participants (program size) in a given year, which affects the volume of incentive payments and level of marketing. In other words, program size and marketing represent the key factors that influence the level of spending in a given year. Marketing costs will vary by type of program. Some programs can be implemented through direct marketing (e.g., mail, email, door-to-door) while others through marketing channels

[17] The program costs do not include incremental participant costs because the focus here is on the program administration costs which represent the costs recovered from ratepayers.

such as equipment distributors as well as retail suppliers. The issue under investigation here is whether or not the level of marketing and hence program cost is affected by the program size and how much of the market has already been reached. With regard to program size, marketing economies of scale could develop as the current period level of effort rises. However, there is a limit to the program size due to measure life of the end-use. For example, if a heat pump has a 20 year life, not all of the heat-pumps in a utility's service area become available for replacement at a given point in time. Instead, in this example, one can expect that 5% (1/20) of the heat pumps will be replaced each year. While there may be marketing cost efficiency gains in a given year, there is a natural limit based on the available equipment turnover[18]. In addition, as market penetration increases, energy efficiency implementation costs are expected to rise at higher levels of penetration of the market. The degree of impacts on program costs, from these factors, is a question to be empirically analyzed.

In addition to historical market penetration, other drivers that could potentially affect the level of program costs are the level of electric rates and the health of the economy. Regarding customer electric rates, the issue to be investigated here is the whether or not higher electric rates make it easier to market energy efficiency measures. With higher electric rates, the customer bill savings would be greater, thus reducing the payback period and making the investment in energy efficiency more cost-effective for the participating customer. With respect to the health of the economy, many economic measures could be used. The issue at question is whether or not it is tougher to market energy efficiency when the economy is under stress, e.g., during a recession or its aftermath. Since the Great Recession ended in 2009, economic growth has been lackluster and unemployment levels have remained elevated. One could contend that higher unemployment rates make it harder to market energy efficiency because energy consumers do not have the spare

[18] The volume of replacements in this example could exceed 5% if the incentives encourage customers to perform early replacement before the end of the useful life. However, these situations are not the typical expectation.

funds to invest in more efficient equipment. Conversely, one could contend that marketing energy efficiency is easier because energy consumers need to find ways to cut costs. Evidence of a relationship between program costs and electric rates and/or economic health can be explored empirically.

4. General Model Development

Assuming that energy efficiency program costs are affected by program size, historical market penetration, electric rates, and health of the economy, then a model can be specified as follows:

$$Program\ Cost = f(Market\ Size, Market\ Penetration, Electric\ Rate, Economic\ Health) \quad (1)$$

To assess the impact of these factors on program cost first requires obtaining data that can facilitate the analysis. As previously mentioned, the EIA has been collecting aggregate data for each utility jurisdiction on the impacts and costs associated with implementing energy efficiency. A discussion of the data as well as its limitations will be provided in the next section. However, the model variables need further specification for clarity prior to the actual data collection.

To compile a dataset for analysis, the definition of the variables is critical. For purposes of analysis, given the types of data available from the EIA data base, the following variable definitions will be employed:

Dependent variable:

Program cost includes the level of direct program spending (dollars) on energy efficiency programs only. Indirect costs are not included.

Independent variables:

Program size refers to the current year achievement of energy impacts as a percent of current year retail kWh sales. As program size increases, one expects the cost to increase, though it may not be an equal proportional increase due to the potential for marketing efficiencies. For example, the current year market size achieved may be 1% of retail sales in one geographic area, but in another geographic area it may be 2% of retail sales. By studying the relative impact on program spending across multiple areas with different levels of achievement, one can begin to understand how costs change as the size of the program increases.

Market penetration represents the cumulative achievement of energy efficiency sales as a percent of retail kWh sales. For this variable, as the market penetration increases and the available market potential begins to be depleted, the cost to reach deeper into the market potential may increase due to the higher cost to acquire participants who may find that the energy efficiency program offers are less interesting or compelling relative to other demands on their time and financial resources. An analysis of program spending between areas with lower market penetration versus higher market penetration may provide insights on how costs change relative to changes in market penetration.

Electric rate reflects the cost of power ($/kWh) to customers in an area. The electric rate drives the level of bill savings from implementation of the energy efficiency measures. The higher the electric rate, the easier it is for a participant to cost-justify investment in energy efficiency because the bill savings generated by the energy efficiency are greater. In this situation, higher electric rates should make it easier and less costly to market the energy efficiency programs. Including a measure of the average cost of electricity in a region should aid in understanding whether or not electric rates impact energy efficiency marketing.

Health of the economy, the final independent variable under consideration here, can be measured in a number of different ways. For example, the rates of growth in employment, per capita disposable income, or gross national product are all reasonable candidates. At the same time, the unemployment rate provides a good measure of overall economic health that is contemporaneous and reflects the state of consumer well-being as well as business confidence. The interesting issue is whether or not a higher unemployment rate indicates greater difficulty funding energy efficiency or lower difficulty. On the surface, higher unemployment rates would seem to imply that consumers have less cash to invest in energy efficiency, thus potentially raising marketing costs. Conversely, it could also mean that there is more demand for energy efficiency as a way to reduce operating costs. Analysis of this factor should also improve understanding of the drivers of program costs.

In general form, Equation 1 can be re-written as an econometric model as follows:

$$PC = \alpha + \beta 1 \cdot CPR + \beta 2 \cdot CPT + \beta 3 \cdot EP + \beta 4 \cdot UR + \varepsilon \quad (2)$$

where:

PC	=	Program cost or spending
CPR	=	Current kWh impacts as a percent of retail sales
CPT	=	Cumulative kWh impacts as a percent of retail sales
EP	=	Average retail price of electricity adjusted for inflation (real dollars)
UR	=	National unemployment rate
ε	=	Error term

This represents the general form of the econometric model to be developed. It is expected, on an a priori basis, that the signs of the coefficients should be: $\beta 1 > 0$; $\beta 2 > 0$; $\beta 3 < 0$; and $\beta 4 > or < 0$.

The data for the model development will come from the EIA data base as well as national data on the unemployment rate and inflation.

5. Model Data

The Energy Information Administration's (EIA) Form 861 has been utilized to collect a wealth of information on energy efficiency and demand response program spending and load impacts. The EIA data for the years 1990 through 2012 may be found on the EIA website. It contains information on a number of items for each utility service area including the following:

- Direct spending on energy efficiency programs
- Direct spending on load management (demand response or demand side management (DSM)) programs
- Indirect program spending – costs not directly related to a specific program
- Incremental energy efficiency MWH and MW – current year annualized load impacts
- Annual energy efficiency MWH and MW – cumulative load impacts
- Incremental demand response MWH and MW – current year annualized load impacts
- Annual actual demand response MWH and MW – cumulative load impacts
- Incremental potential[19] demand response MWH and MW – cumulative load impacts
- Annual potential demand response MWH and MW – cumulative load impacts
- Information is also available on retail revenues and MWH sold to ultimate customers for each utility service area[20]

[19] Potential impacts reflect the expected load reductions under normal extreme weather conditions as opposed to the actual reductions achieved given the actual weather conditions.
[20] Revenues and sales for utility service areas in deregulated markets require careful handling to ensure a complete picture of revenues and sales.

- Information is also available on state level retail revenues and MWH sold to ultimate customers on EIA Form 826

Data on national inflation and unemployment may be found from numerous sources[21].

Unfortunately, the data collected through the use of EIA Form 861 has several limitations. These limitations include lack of information on the life of the measures in the portfolio of programs, consistency in reporting over time, consistency in treating effects such as free-riders, consistency in reporting program costs versus indirect costs, and impacts due to changes over time in the structure and instructions associated with Form EIA 861.

With respect to measure life, Form EIA 861 seeks data on current year annualized incremental impacts. However, the life expectancy of those impacts is unknown. Impacts from some measures could last 20 years while other associated with behavioral type programs might last just one year and require constant reinforcement to maintain the impacts. For this reason, the analysis conducted here looks at total annual spending relative to the first year impacts. Trying to compute a levelized cost requires knowledge that is just not available. While one might intuit an expected measure life for a portfolio, it is only a guess and could lead to misleading conclusions. In reviewing the EIA data, it is apparent that the reporting is not consistent. For example, kWh could be reported instead of MWH or dollars instead of thousands of dollars as specified in the instructions to the form. For this reason, this study will focus on the last three years of data for the years 2010 through 2012. Use of the most recent data should provide the best quality of data from the data base.

Regarding cost data, it is unclear what could be included in indirect costs. The categorization of costs across utility service areas will certainly be different, especially with respect

[21] See the website Freelunch.com sponsored by Moody's Analytics for general macroeconomic data including inflation and unemployment.

to treatment of overheads and utility financial incentives. For purposes of this study, only the direct program costs including incentive payments to participants will be considered in the analysis. Finally, to facilitate the research, costs and impact data is aggregated to a state level[22]. This provides a useful data set for the 50 states plus the District of Columbia.

6. Model Development

Using data for the period 2010 to 2012 opens the possibility of taking two approaches to the analysis. In attempting to glean from the data how costs are affected by program size and market penetration, use of multiple approaches can help put a range around an issue afflicted with a lot of uncertainty.

The first approach involves using all the state level data for the 2010 to 2012 time period. This involves estimating a cross-sectional / time-series model. It is cross-sectional given use of data for the 50 states plus the District of Columbia. It is time-series since it covers the period 2010 to 2012. To estimate this model over time with the cross-section requires the use of a fixed-effects panel data modeling approach that captures the underlying relationship between cost and the independent variables while letting the intercept terms capture the inherent underlying differences across the various geographies. The model estimates a separate intercept term for each of the 51 geographic areas while developing estimates for the independent variables that are the same for all the geographic areas. The methodology is designed to uncover the fundamental relationship between cost and the independent variables while differences in the characteristics of each geographic area are captured in the intercept terms.

Algebraically, Model 1, the fixed-effect panel data model, is described as follows:

$$PC_{it} = \alpha_i + \beta 1 \cdot CPR_{it} + \beta 2 \cdot CPT_{it} + \beta 3 \cdot EP_{it} + \beta 4 \cdot UR_t + \varepsilon_{it}) \qquad (3)$$

22 Future research will extend this analysis to an individual utility service area.

where:

PC_{it}	=	Program costs for geography i during year t
α_i	=	Constant term for geography i (the fixed-effect)
CPR_{it}	=	Current kWh impacts as percent of retail sales for geography i during year t
CPT_{it}	=	Cumulative kWh impacts as percent of retail sales for geography i during year t
EP_{it}	=	Real electricity price for geography i during year t
UR_t	=	National unemployment rate for year t
ß	=	Estimated coefficients for ß1, ß2, ß3, and ß4
ε	=	Error term for geography i during year t.

The second approach involves using all the data for the most recent year, 2012[23]. This is a traditional cross-sectional approach. Cross-sectional models are extremely useful because they provide a view into the long-run since the data contains multiple points along the continuum of experience. This approach does not require the use of the fixed effects panel data approach. Instead, the model can be estimated using a traditional application of ordinary least squares regression. The model to be estimated is the same as that previous presented by Equation 2.

Algebraically, Model 2, the cross-sectional model, is described as follows:

$$PC_i = \alpha + \beta 1 \cdot CPR_i + \beta 2 \cdot CPT_i + \beta 3 \cdot EP_i + \varepsilon \quad (4)$$

where:

[23] Data for Delaware and Louisiana were deleted since the EIA data indicates essentially zero cumulative impacts for the year 2012.

PC_i = Program cost or spending for geography i

CPR_i = Current kWh impacts as a percent of retail sales for geography i

CPT_i = Cumulative kWh impacts as a percent of retail sales for geography i

EP_i = Real average retail price of electricity for geography i

ε_i = Error term for geography i

The one difference from Equation 2 is that the national variable UR is removed since it would be the same in a given year for all geographic regions.

7. Model Results

Both models were estimated in logarithmic form using the data previously described. The benefit of estimating the model in logarithmic form is that the coefficients represent elasticities that enable one to compute how a percent change in the independent variable results in a coefficient adjusted percent change in the level of program costs. Table 1 below summarizes the results of the statistical analysis for both Model 1 and Model 2.

Table 1			
Model 1			
Variable	Coefficient	t-statistic	Stat Significance
Log (CPR)	0.609	7.761	Yes
Log (CPT)	0.278	3.293	Yes
Log (EP)	-11.980	-1.863	Yes
Log (UR)	2.438	0.769	No
Adjusted R-squared	0.759		Yes
Model 2			
Variable	Coefficient	t-statistic	Stat Significance
Log (CPR)	-0.003	-0.055	No
Log (CPT)	0.897	6.865	Yes
Log (EP)	-0.837	-1.527	Yes at 7% level
Adjusted R-squared	0.543		Yes

For Model 1, the results indicate that strong statistical relationships exist between the level of program cost and program size, market penetration, and real electric price. All three independent variables are statistically significant using a one-tail test given the a priori view of the expected sign for the variables. Only the unemployment rate variable was not statistically significant.

For Model 2, the results indicate that strong statistical relationships exist between the level of program cost and market penetration, and real electric price. The market penetration variable is strongly significant, while the electric price variable is weakly significant. The program size variable is not significant in this model.

These results provide a first insight into the relationship between program costs and program size and market penetration. While the data is aggregate, these results do indicate how these costs can be expected to change. At this point in time, no other study has generated these types of results and insights.

The following section provides an example of how the results can be used to forecast program costs as market penetration increases.

8. Model Application

Often under an Energy Efficiency Resource Standard, there is a requirement to achieve X% cumulative load reduction by a specific year or to reduce load 1% per year for some number of years. Sometimes these values are based upon the results of a market potential study. As an example, let's assume a market potential study concluded that the economic potential over a 20 year period was 20%, or 1% per year. Then, the question becomes: how does the program cost change as one begins to achieve impacts that approach the economic potential, keeping in mind that economic potential implies that 100% of the cost-effective measures are installed?
Given both econometric models previously presented, simulations of the cost impacts can be performed under each model to provide a range on how costs could change as market penetration increases. Another factor to consider is the achievable potential. Data in the EPRI market potential studies[24] indicate that approximately 50% of the economic potential is realistically achievable and that 75% of the economic potential would represent a high achievable potential. Tables 2 and 3 provide examples of how the coefficients from each model can be used to estimate how costs increase as the market penetration increases. Given an economic market potential of 20% of retail sales or 1% per year for 20 years, the achievable potential would be 10% or 0.5% per year, and the high potential would be 15% or .75% per year. The tables depict how average costs change when the market penetration of energy efficiency increases from 50% to 75%.

[24] This applies in the 10 to 20 year time frame. See reference numbers 24 and 25.

Table 2: Impact of Changes in Market Penetration on Program Costs
Simulation of Model 1
Key Assumptions:

Assume the economic market potential is 20% of retail sales.
If the achievable potential is 50% of the market potential, then the achievable potential represents 10% of retail sales.
Increasing achievement from 50% of the market potential to 75% of the market potential impacts the unit cost of EE.
First year cost per kWh saved starts at $.20/kWh
Incremental annual impacts are 1% of retail sales or 100,000,000 kWh per year
The current cumulative market penetration starts at 3% to reflect some existing market presence

EE as % of Retail Sales					Change in Costs
Incremental Impact	Cumulative	Costs (Real $)	Incremental kWh	$/kWh	Due to Change in Cumulative %
1.0%	3.0%	$ 20,000,000	100,000,000	$ 0.2000	
1.0%	4.0%	$ 21,853,333	100,000,000	$ 0.2185	$ 1,853,333
1.0%	5.0%	$ 23,372,140	100,000,000	$ 0.2337	$ 1,518,807
1.0%	6.0%	$ 24,671,631	100,000,000	$ 0.2467	$ 1,299,491
1.0%	7.0%	$ 25,814,750	100,000,000	$ 0.2581	$ 1,143,119
1.0%	8.0%	$ 26,839,964	100,000,000	$ 0.2684	$ 1,025,214
1.0%	9.0%	$ 27,772,653	100,000,000	$ 0.2777	$ 932,689
1.0%	10.0%	$ 28,630,519	100,000,000	$ 0.2863	$ 857,866
1.0%	11.0%	$ 29,426,448	100,000,000	$ 0.2943	$ 795,928
1.0%	12.0%	$ 30,170,134	100,000,000	$ 0.3017	$ 743,687
1.0%	13.0%	$ 30,869,076	100,000,000	$ 0.3087	$ 698,941
1.0%	14.0%	$ 31,529,199	100,000,000	$ 0.3153	$ 660,123
1.0%	15.0%	$ 32,155,279	100,000,000	$ 0.3216	$ 626,080
1.0%	16.0%	$ 32,751,223	100,000,000	$ 0.3275	$ 595,945
1.0%	17.0%	$ 33,320,276	100,000,000	$ 0.3332	$ 569,053
1.0%	18.0%	$ 33,865,161	100,000,000	$ 0.3387	$ 544,885
1.0%	19.0%	$ 34,388,189	100,000,000	$ 0.3439	$ 523,029
1.0%	20.0%	$ 34,891,343	100,000,000	$ 0.3489	$ 503,154
1.0%	21.0%	$ 35,376,332	100,000,000	$ 0.3538	$ 484,990
1.0%	22.0%	$ 35,844,648	100,000,000	$ 0.3584	$ 468,315

Cost per first year kWh for 50% of economic potential		Cost per first year kWh for next 25% of economic potential	
Total Cost	$ 198,954,991	Total Cost	$ 154,150,136
kWh for 50%	800,000,000	kWh for next 25% of retail sales	500,000,000
Cost per first year kWH	$ 0.249	Cost per first year kWH	$ 0.308
		Percent increase in unt cost	24%
Model Elasticities			
Incremental	0.609		
Cumulative	0.278		

Table 3: Impact of Changes in Market Penetration on Program Costs
Simulation of Model 2
Key Assumptions:

Assume the economic market potential is 20% of retail sales.
If the achievable potential is 50% of the market potential, then the achievable potential represents 10% of retail sales.
Increasing achievement from 50% of the market potential to 75% of the market potential impacts the unit cost of EE.
First year cost per kWh saved starts at $.20/kWh
Incremental annual impacts are 1% of retail sales or 100,000,000 kWh per year
The current cumulative market penetration starts at 3% to reflect some existing market presence

EE as % of Retail Sales					Change in Costs
Incremental Impact	Cumulative	Costs (Real $)	Incremental kWh	$/kWh	Due to Change in Cumulative %
1.0%	3.0%	$ 20,000,000	100,000,000	$ 0.2000	
1.0%	4.0%	$ 25,980,000	100,000,000	$ 0.2598	$ 5,980,000
1.0%	5.0%	$ 31,806,015	100,000,000	$ 0.3181	$ 5,826,015
1.0%	6.0%	$ 37,512,014	100,000,000	$ 0.3751	$ 5,705,999
1.0%	7.0%	$ 43,120,060	100,000,000	$ 0.4312	$ 5,608,046
1.0%	8.0%	$ 48,645,588	100,000,000	$ 0.4865	$ 5,525,528
1.0%	9.0%	$ 54,099,974	100,000,000	$ 0.5410	$ 5,454,387
1.0%	10.0%	$ 59,491,939	100,000,000	$ 0.5949	$ 5,391,964
1.0%	11.0%	$ 64,828,365	100,000,000	$ 0.6483	$ 5,336,427
1.0%	12.0%	$ 70,114,824	100,000,000	$ 0.7011	$ 5,286,459
1.0%	13.0%	$ 75,355,907	100,000,000	$ 0.7536	$ 5,241,083
1.0%	14.0%	$ 80,555,465	100,000,000	$ 0.8056	$ 5,199,558
1.0%	15.0%	$ 85,716,768	100,000,000	$ 0.8572	$ 5,161,304
1.0%	16.0%	$ 90,842,631	100,000,000	$ 0.9084	$ 5,125,863
1.0%	17.0%	$ 95,935,496	100,000,000	$ 0.9594	$ 5,092,865
1.0%	18.0%	$ 100,997,504	100,000,000	$ 1.0100	$ 5,062,008
1.0%	19.0%	$ 106,030,547	100,000,000	$ 1.0603	$ 5,033,042
1.0%	20.0%	$ 111,036,305	100,000,000	$ 1.1104	$ 5,005,758
1.0%	21.0%	$ 116,016,283	100,000,000	$ 1.1602	$ 4,979,978
1.0%	22.0%	$ 120,971,836	100,000,000	$ 1.2097	$ 4,955,553

Cost per first year kWh for 50% of economic potential		Cost per first year kWh for next 25% of economic potential	
Total Cost	$ 320,655,590	Total Cost	$ 376,571,330
kWh for 50%	800,000,000	kWh for next 25% of retail sales	500,000,000
Cost per first year kWH	$ 0.401	Cost per first year kWH	$ 0.753
		Percent increase in unt cost	88%
Model Elasticities			
Incremental	0		
Cumulative	0.897		

Under Model 1, the average cost increases from \$0.249/kWh to \$0.308/kWh or 24%. Under Model 2, the cost increases from \$0.401/kWh to \$0.753/kWh or 88%. The key point here is not the size of the unit cost numbers, but the percent increase. These values produce a range of average cost increases of 24% to 88% as market penetration increases. This is a wide range, but is based on actual program cost experience. It provides guidance on the expectation that as the market penetration of energy efficiency increases, the unit cost increases.

9. Implications for Future Research

From the review of other studies, it is apparent that little to no evidence exists on the relationship between program costs, program size, and market penetration. But now, the research conducted in this study provides an initial insight into this relationship. While the range of estimated impacts on cost is rather wide, selecting a market penetration driven percent increase in energy efficiency costs in the middle of the range seems appropriate. This percent increase would be applied in estimating costs when the program impacts are expected to exceed the achievable potential. At the same time, efforts to improve targeted marketing can help with cost management.

It should be obvious that further research in this area is warranted. As mentioned, this study is the first to investigate how costs can rise with increases in program size and market penetration. The findings point to the existence of cost efficiencies with respect to program size, but rising costs as market penetration increases. The results developed here are at a very high level. The potential for greater insights may exist by monitoring individual program costs over time. Future research along that direction seems appropriate. The results could vary significantly from one program to the next. Analysis could also be conducted at the portfolio level for individual utility energy efficiency efforts or a cross-section of individual utilities. Only through further research can the range be narrowed and/or confirmed.

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