Moving Towards an 8760 TRM

Creating Time-Differentiated Energy Savings Estimates

Claude Godin, Principal Consultant

October 19th, 2022

WHEN TRUST MATTERS

Agenda

Introductions

TRM defined

Why move to TRM 8760?

TRM 8760 for planning and forecasting

Leveraging AMI data to inform TRM estimation

Operationalizing AMI Data for program delivery

Introductions

Claude Godin

Mr. Godin has over 40 years' experience in the energy market, specializing in the design and delivery of large-scale projects, meter data acquisition/ management, and energy analytics. Most recently, Mr. Godin has been under contract with a large Middle East Regulator to assess and audit the deployment of a 10-million-point AMI deployment. The project included assessing the current state of the systems implemented and the quality and performance of their integration, the performance of the metering and communication technologies deployed, and the state and quality of the field installations. Other recent projects include building a business case for a large distribution company in Australasia in support of gaining access to AMI data currently owned by retailers; developing a business case and road map for the implementation of a new load research department at a water and electric utility; implementing one of the world's largest water and electric end use studies in support of new bottom-up forecasting systems; and designing a new interval data processing platform for DNV's Load Analytics as a Service product offering.

Wesley Whited

Wesley Whited has been innovating in the lighting industry for the past decade with professional experience in utility program design, technical strategy, and project management. As a lighting specialist, Mr. Whited oversaw the specification and implementation of many large-scale, complex commercial lighting and controls projects as both a lighting rep and electrical distributor. As a member of DNV's Program Design and Implementation team, Mr. Whited leads a cross-functional team of engineers who design utility clean-tech programs around internet-enabled technologies. Mr. Whited is a recognized thought-leader in the field of Networked Lighting and IoT technologies and sits on technical committees for the Design Lights Consortium (DLC), and ANSI. He has published three papers in academic journals and has presented on behalf of DNV at multiple conferences, frequently speaking about the integrating customer devices to the electric grid. He holds a BA from West Virginia University (WVU) and an MBA from Capital University. He lives in Asheville NC with his wife and two dogs.

Thomas Quasarano

Thomas Quasarano leads **Consumers Energy** business partner relationships, with responsibility for partner relationships within the commercial and industrial energy efficiency programs. He also oversees the company's ongoing efforts into emerging markets and partner relationships. In his previous role with DNV, he served as the Operations Manager leading the Commercial and Industrial portfolio and was the Outreach Manager for 4 years prior to taking on the Operations Manager position. Quasarano was responsible for leading the company's Energy Efficiency programs in the Michigan market. Prior to joining DNV, Quasarano served as a Territory Market manager for Sprint PCS, where he was instrumental in growing revenues within his market by more than 30 percent during a three-year period across Michigan, Indiana, and Kentucky.

Technical Reference Manuals (TRMs) are valuable resources for state regulators, utilities, program administrators, and program implementers for estimating the energy and demand savings of end-use energy efficiency measures.

Traditional TRM & DSM Evaluation Impacts

- TRM based on modeled impacts for efficiency program planning numbers have generally only provided annualized usage and peak hourly demand impacts for the peak season
- TRM are used to set targets for utility DSM programs, which use tracking databases with estimated impacts for annual usage and peak demand only
- DSM evaluations typically refine TRM model values for annual usage and estimate coincident peak contributions

Value of Dynamic TRM and Interval-level Impacts

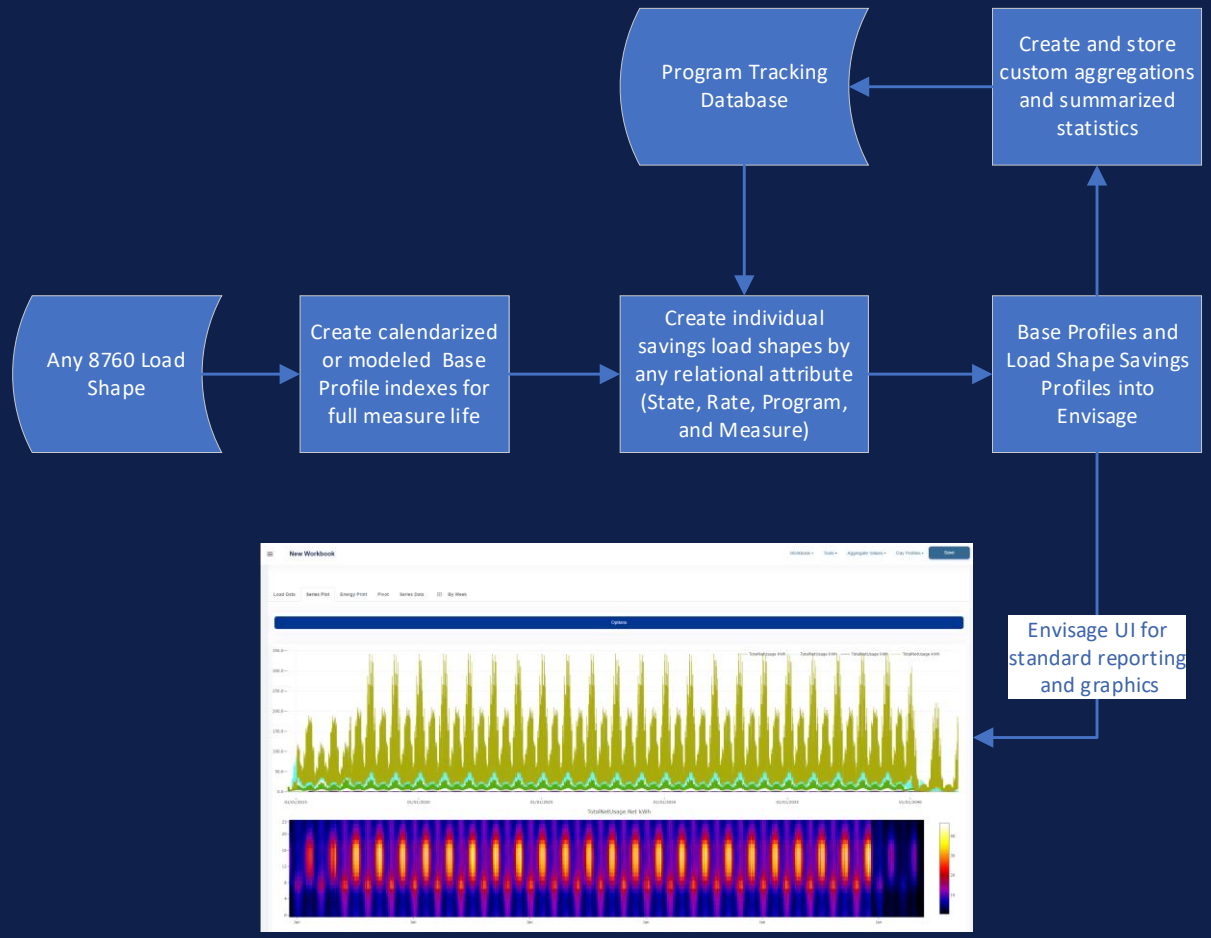
- Enhanced 8760 TRM models can now be developed at the measure-level using end use load shapes based on metered, modeled or borrowed sources
- Measure-level load shapes can be applied to tracking database to phase-in and phase out measure impacts based on measure life
- Provides more accurate interval level measure and program impacts for the life of the programs (back-cast and forecast)
- Interval impacts can be applied to avoided costs, GHG emissions, or production costs to get real cost impacts

DNV

The 8760 TRM

- Valuable resources for state regulators, utilities, and program administrators and implementers
- Converts annual energy savings and peak demand reduction into 8760 savings impacts for use in integrated resource planning and forecasting departments
- Lets the utility understand the true value of demand side resources
- Allows utilities to track and forecast the impact of DSM portfolios using 8760 measure level impacts
- Allows for ad hoc aggregation by jurisdiction, program year, program, end-use, and measure

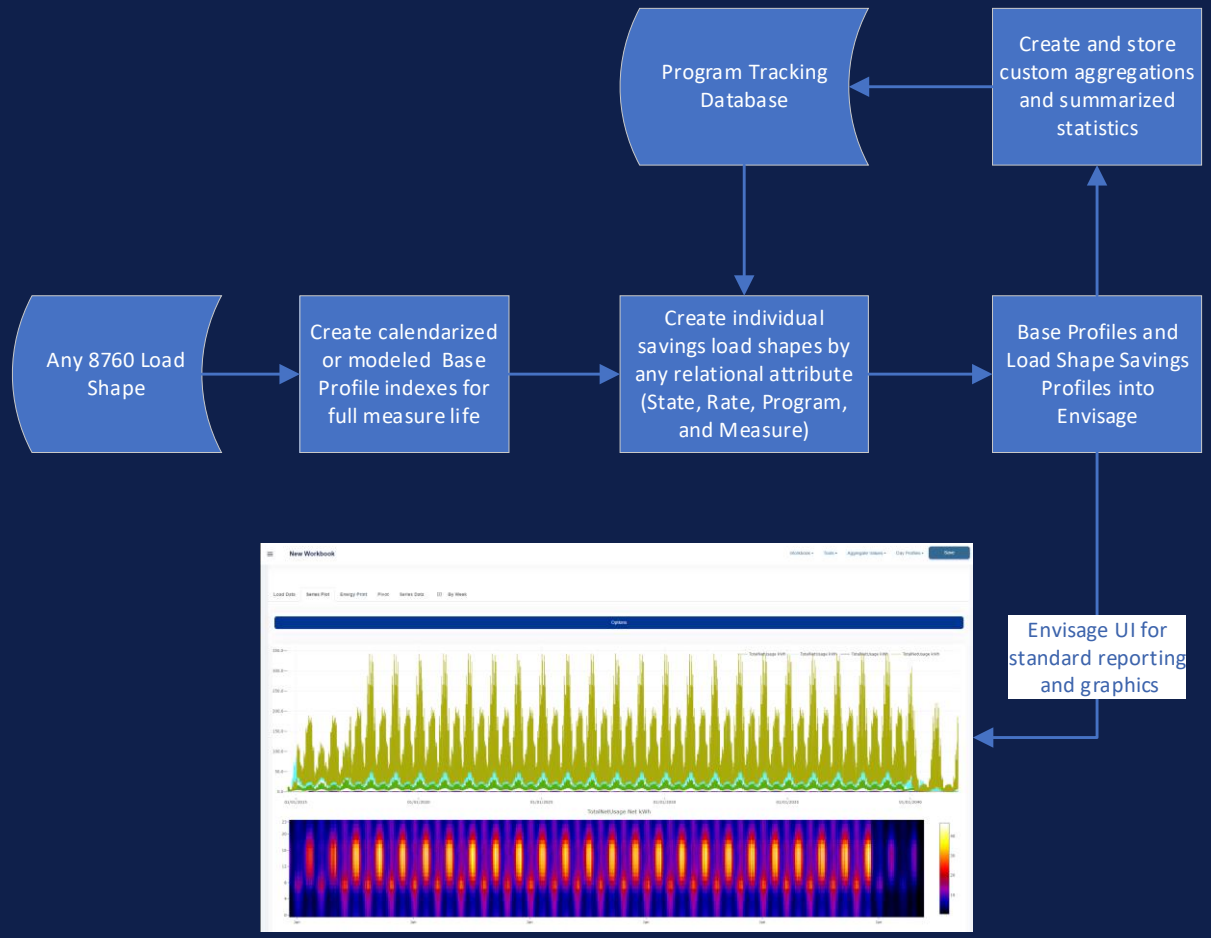
Converting Program Tracking into 8760 Savings Impacts



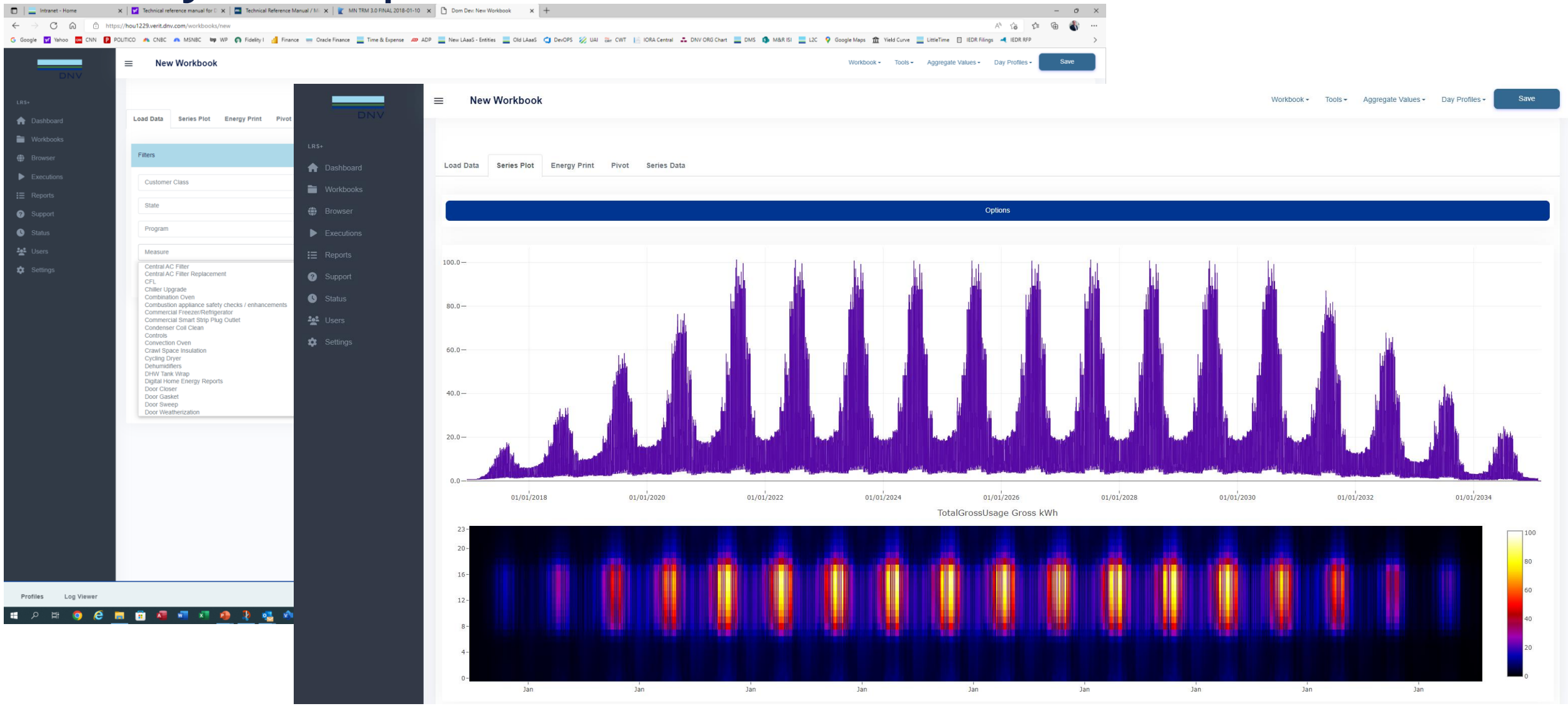
The 8760 Process

- Create database view of tracking database program transactions. Choosing the lowest level of transaction will allow for the derived load shapes to be aggregated to any available relational variable (State, Rate, Program, Customer ID, End Use, or Measure)
- Build library of calendarized base measure load shapes to be assigned to each measure transaction above.
- Covert each tracking database traction into 8760 intervals over the life of the measure.
- Aggregate like-for-like results and store results in database along with relational variables
- Provide rich tool set of reporting and visualization tools to interested enterprise users

Converting Program Tracking into 8760 Savings Impacts

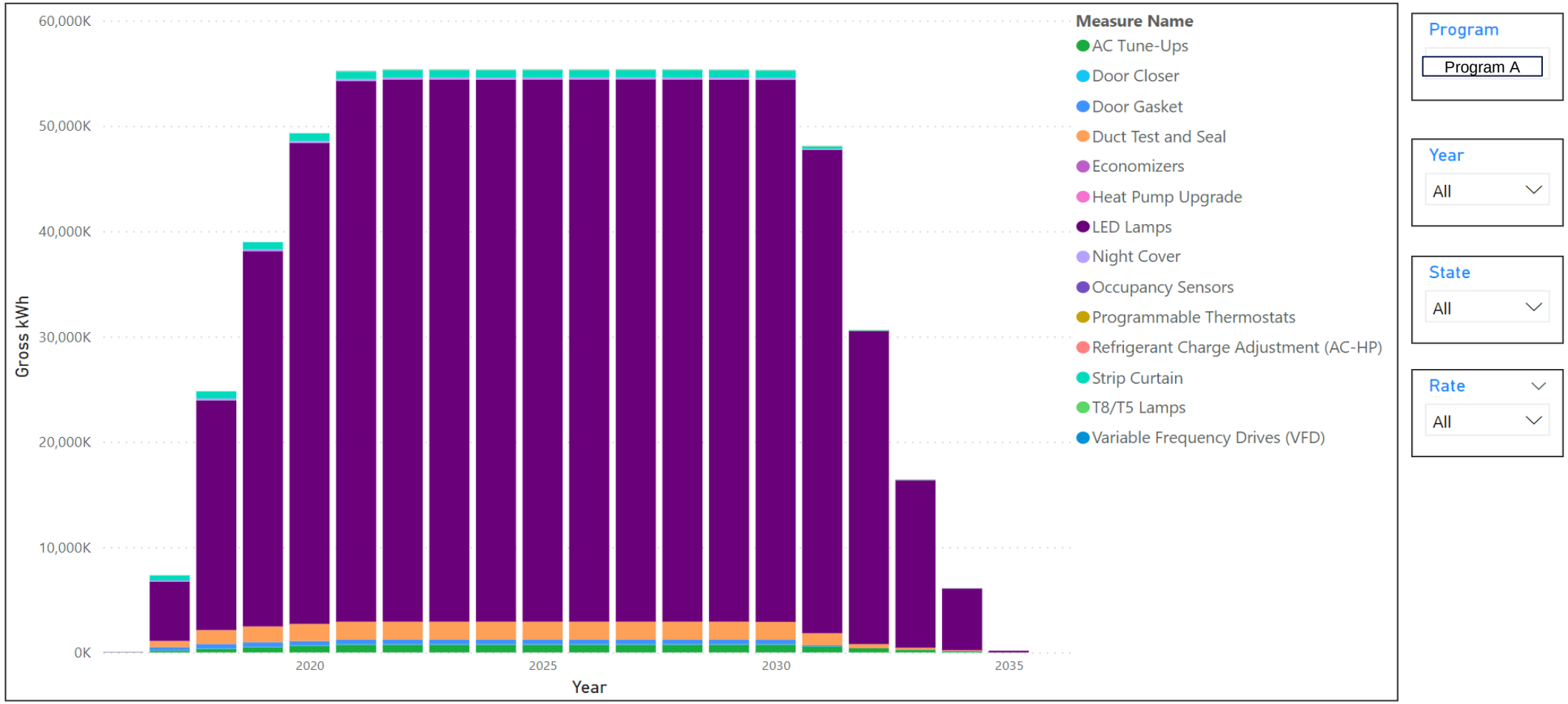


Utility Example

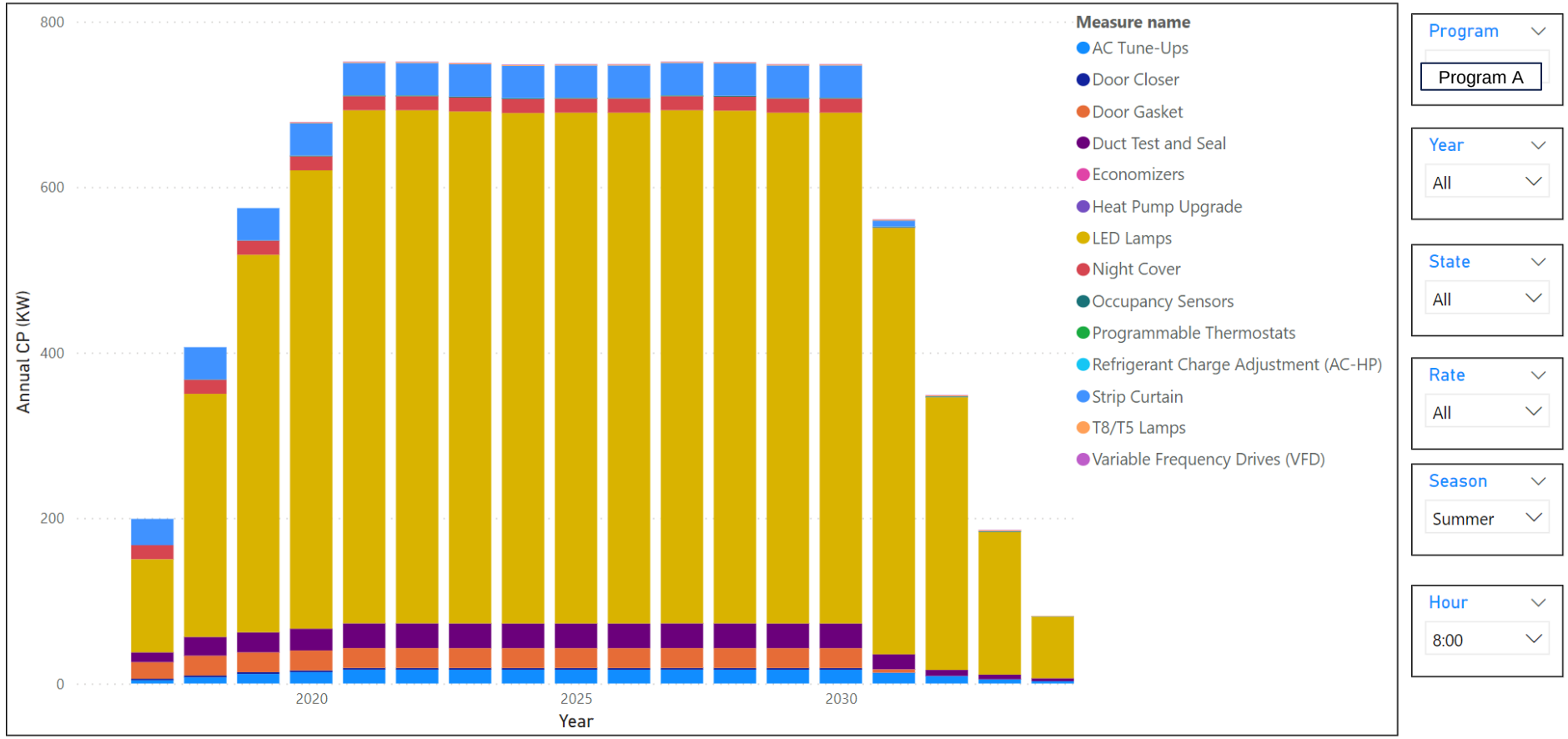


Utility Example kWh Savings

Gross Annual Energy Savings (kWh) by Program/End-Use/Measure and Selected State and Rate



Utility Example Coincidence Peak Savings



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Leveraging AMI Data to Inform TRM Estimation

Prepared by:

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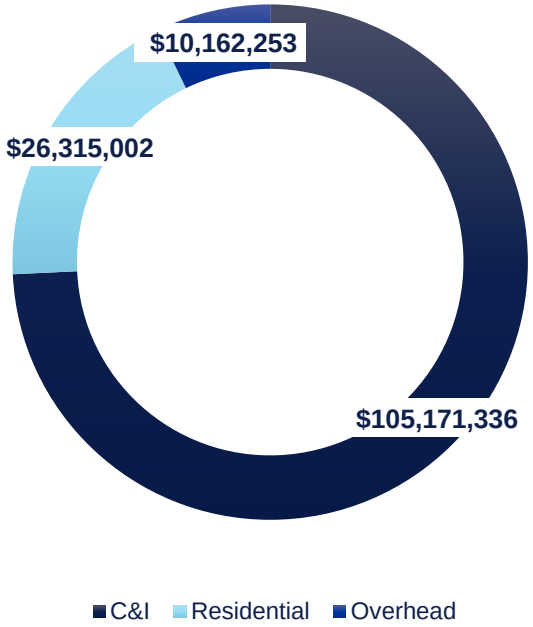
Pilot and Emerging Technologies
DNV Energy Systems

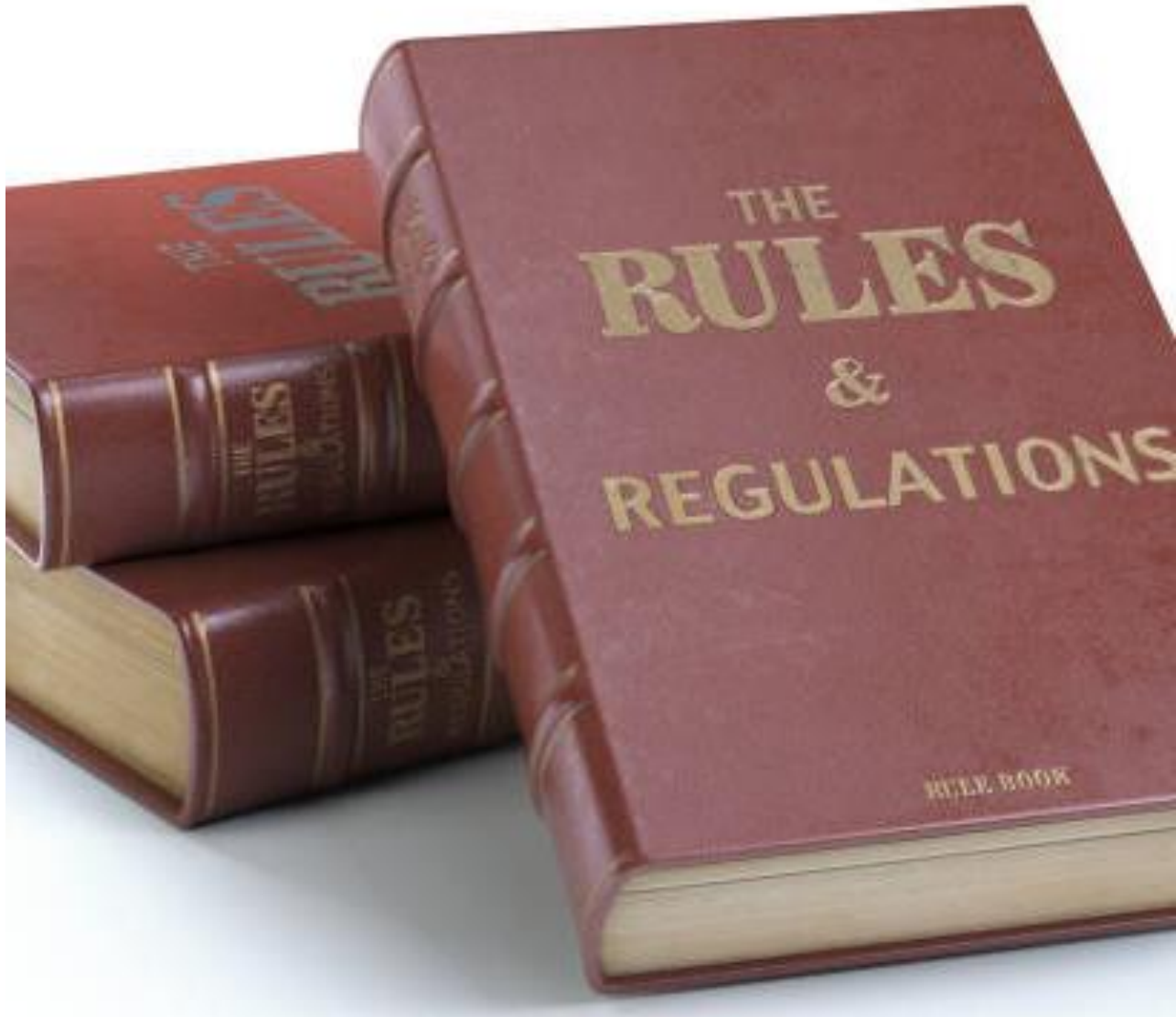
08 September 2022

EE is Big Business

EE Spending by Michigan IOU in 2021



Esource data



Energy Savings Calculation

Algorithms

$$\Delta kW = (\#\ of\ replaced\ fixtures) * (baseline\ fixture\ wattage\ from\ table) - (\#\ of\ fixtures\ installed) * (wattage\ of\ new\ fixture)$$

$$\text{Energy Savings}\left(\frac{kWh}{yr}\right) = (\Delta kW) * \boxed{(Hrs)}$$

$$\text{Peak Demand Savings (kW)} = (\Delta kW) * (CF)$$

TRM Building-Type Assumptions

Building Type	Sector	CF	Hours
Medical - Clinic	Large Commercial/Industrial & Small Commercial	0.8	3,909
Medical - Hospital	Large Commercial/Industrial & Small Commercial	0.8	8,760[30]
Office	Large Commercial/Industrial	0.7	2,969
	Small Commercial	0.67	2,950
Other	Large Commercial/Industrial & Small Commercial	0.66	4,573
Retail	Large Commercial/Industrial	0.96	4,920
	Small Commercial	0.86	4,926
School	Large Commercial/Industrial & Small Commercial	0.50	2,575
Warehouse/ Industrial	Large Commercial/Industrial	0.7	4,116
	Small Commercial	0.68	3,799
Unknown[31]	Large Commercial/Industrial	0.50	2,575

Massachusetts TRM, 2016-2018 Program Years, October 2015. Original source: DNV KEMA (2013). Impact Evaluation of 2010 Prescriptive Lighting Installations. Prepared for Massachusetts Energy Efficiency Program Administrators and Massachusetts Energy Efficiency Advisory Council.

Existing

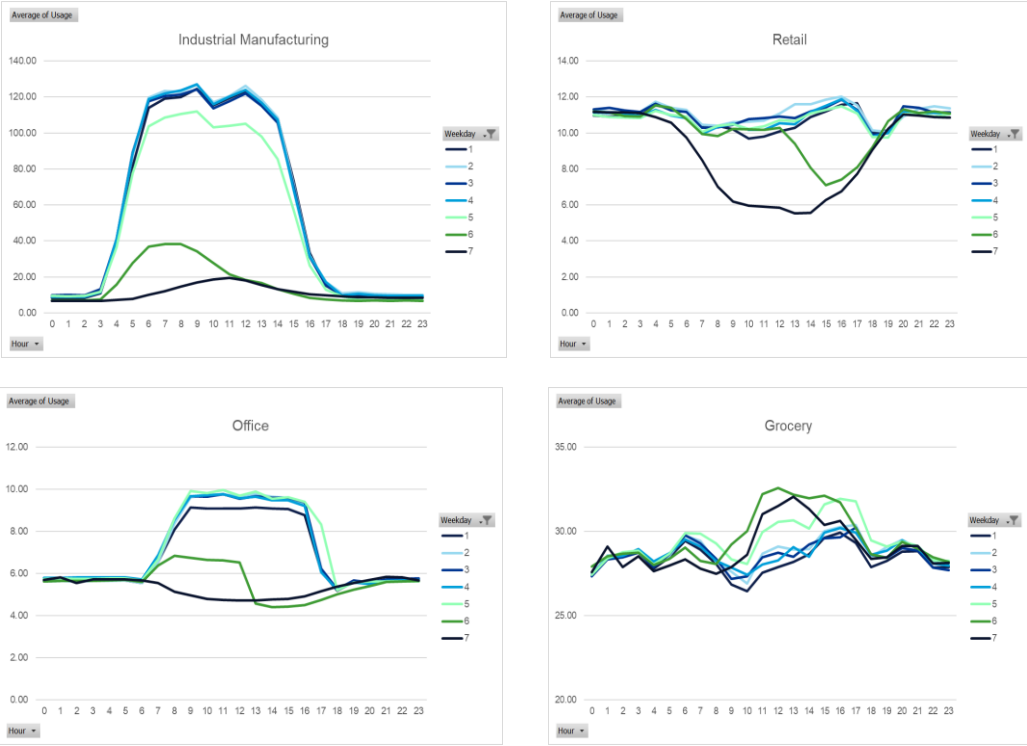
Business Type	HOU
Education	2,239
Grocery	N/A
Health	3,222
Industrial Manufacturing	2,575
Lodging	1,515
Miscellaneous / Other	1,414
Office	1,974
Religious	1,686
Restaurant	4,046
Retail	2,830
Warehouse	3,587
Weighted Value*	**2,744**

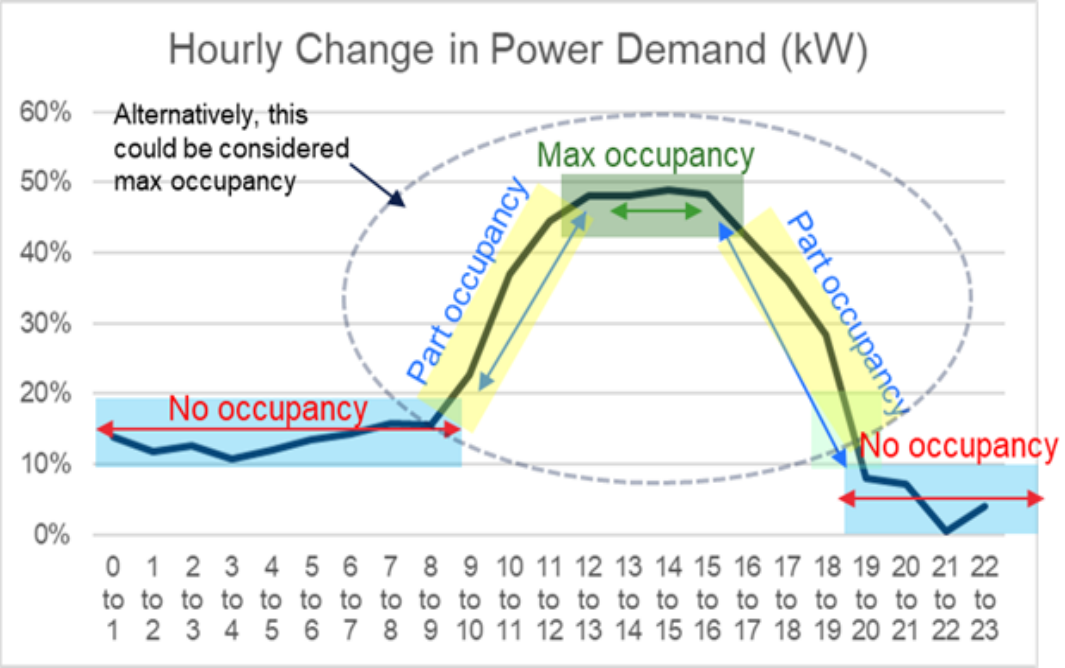
Proposed

	HOU	
Business Type	**Approach A**	**Approach B**
Education	4,294	3,371
Grocery	6,192	5,433
Health	4,764	4,242
Industrial Manufacturing	4,709	3,301
Lodging	5,065	4,385
Miscellaneous / Other	4,096	4,127
Office	4,412	3,683
Religious	3,222	4,663
Restaurant	5,288	4,895
Retail	4,916	5,123
Warehouse	4,565	4,025
Weighted Value*	**4,551**	**4,200**

Process

- Synthesis & Analysis of 300 + C&I AMI data sets based on a sample of ~14,000 unique accounts
- The theory that building occupancy is influenced by hourly power demand is strengthened with the definition of the 8-hour segments
- Two models (Approach A & Approach B) developed to mathematically determine if there is a correlation between power use and states of occupancy

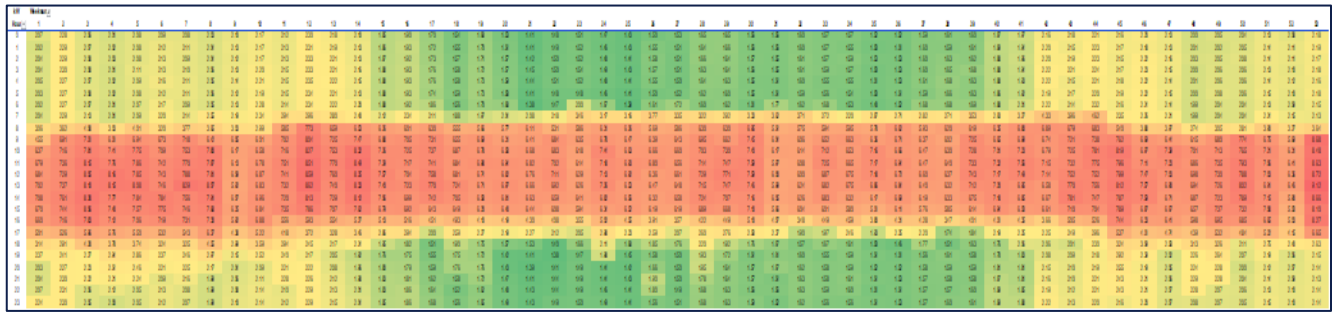




Source: DOE

Approach A

- Heat Mats



- Bin Data

Lower	Upper	Frequency	%			
0	4	755	59%	Hours		3,463
4	9	441	35%			
9	14	76	6%	Min	1	
14	19	0	0%	Max	12	
19	24	0	0%	Range	11	

- For the hours, the first bin captures values representing the lowest 25% of values inside the table. These values are being considered as “off” hours. The remainder of the time the building is assumed to be “on”. The individual bin frequency divided by the total frequency will result in a % frequency for each bin.

Q1 = Min + (Range/4) = 1 + 8/4 = 3

Annual hours = {(Σ %frequency - % frequency1)*(8,760 – 10*24)}

Approach B

- 8-hour segments

	Full Date	Year	Month	Day	Hour	Usage
SEGMENT 1	2018-01-01	2018	01	01	0:00	6.4
	2018-01-01	2018	01	01	1:00	6.4
	2018-01-01	2018	01	01	2:00	6.4
	2018-01-01	2018	01	01	3:00	6.4
	2018-01-01	2018	01	01	4:00	6.4
	2018-01-01	2018	01	01	5:00	6.2
	2018-01-01	2018	01	01	6:00	6.4
	2018-01-01	2018	01	01	7:00	6.3
SEGMENT 2	2018-01-01	2018	01	01	8:00	6.3
	2018-01-01	2018	01	01	9:00	6.3
	2018-01-01	2018	01	01	10:00	6.2
	2018-01-01	2018	01	01	11:00	6.4
	2018-01-01	2018	01	01	12:00	6.3
	2018-01-01	2018	01	01	13:00	6.0
	2018-01-01	2018	01	01	14:00	5.7
	2018-01-01	2018	01	01	15:00	5.5
SEGMENT 3	2018-01-01	2018	01	01	16:00	5.5
	2018-01-01	2018	01	01	17:00	5.3
	2018-01-01	2018	01	01	18:00	5.4
	2018-01-01	2018	01	01	19:00	4.9
	2018-01-01	2018	01	01	20:00	5.6
	2018-01-01	2018	01	01	21:00	5.8
	2018-01-01	2018	01	01	22:00	6.1
	2018-01-01	2018	01	01	23:00	6.0

	Average	Standard deviation
SEGMENT 1	6.3	0.048
SEGMENT 2	6.1	0.311
SEGMENT 3	5.6	0.379

Primary algorithms:

a. If $(M_C + SD_C) < (M_S - SD_S)$, occupancy factor is 1

b. If $(M_C - SD_C) > (M_S + SD_S)$, occupancy factor is 0

c. If neither statement is true, O_P = occupancy factor of previous segment (0 or 1)

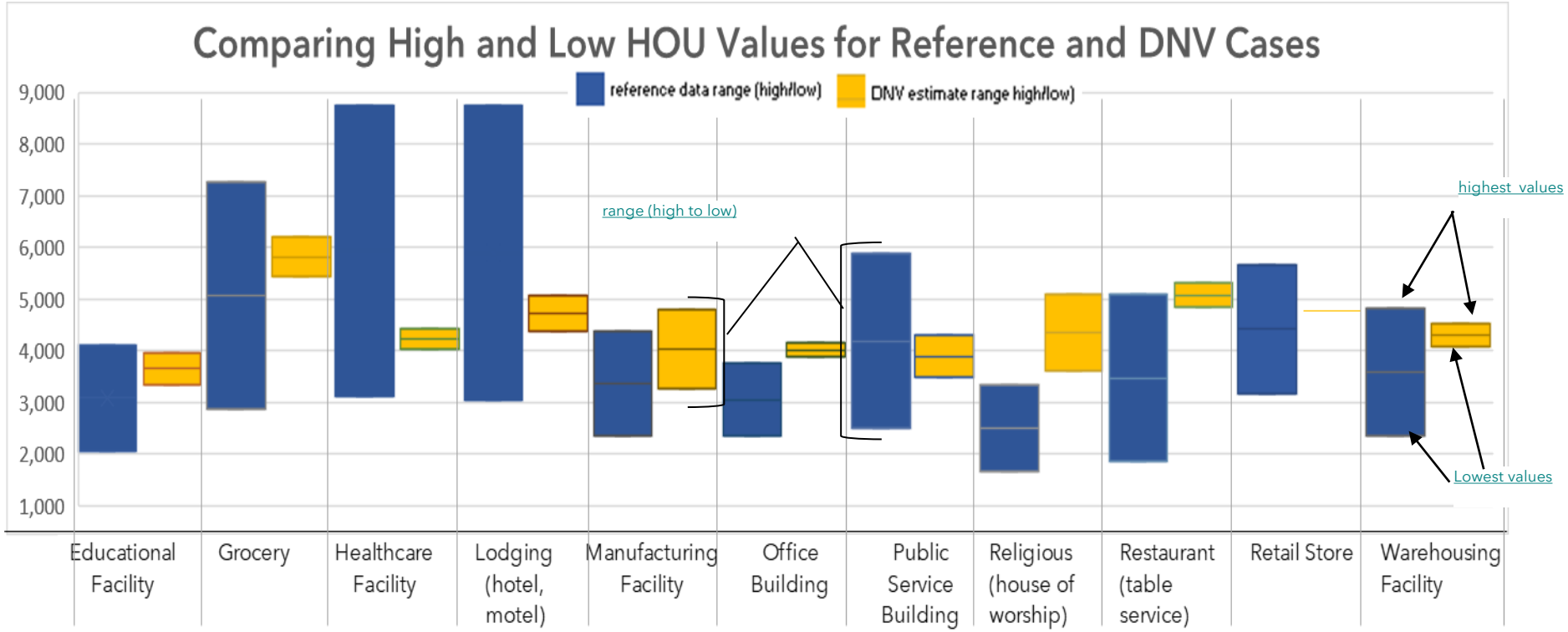
There are three potential outputs from these algorithms:

a. 1 – indicates occupancy

b. 0 – indicates unoccupied

c. No change. Use the value from the previous state (1 or 0)

DNV vs Industry References

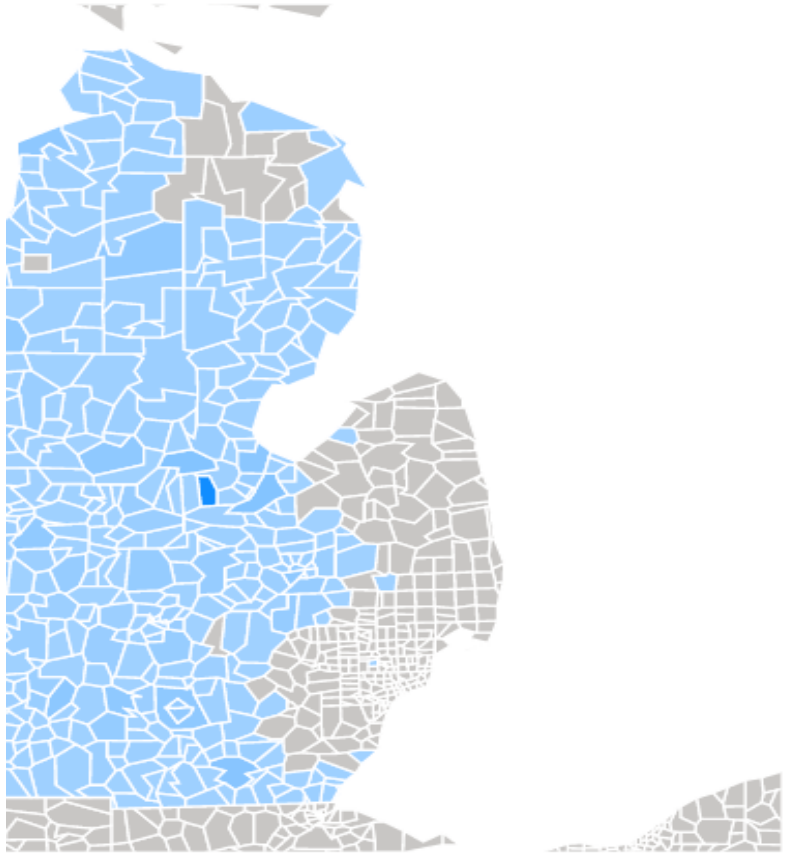


Operationalizing AMI Data

The Big Picture

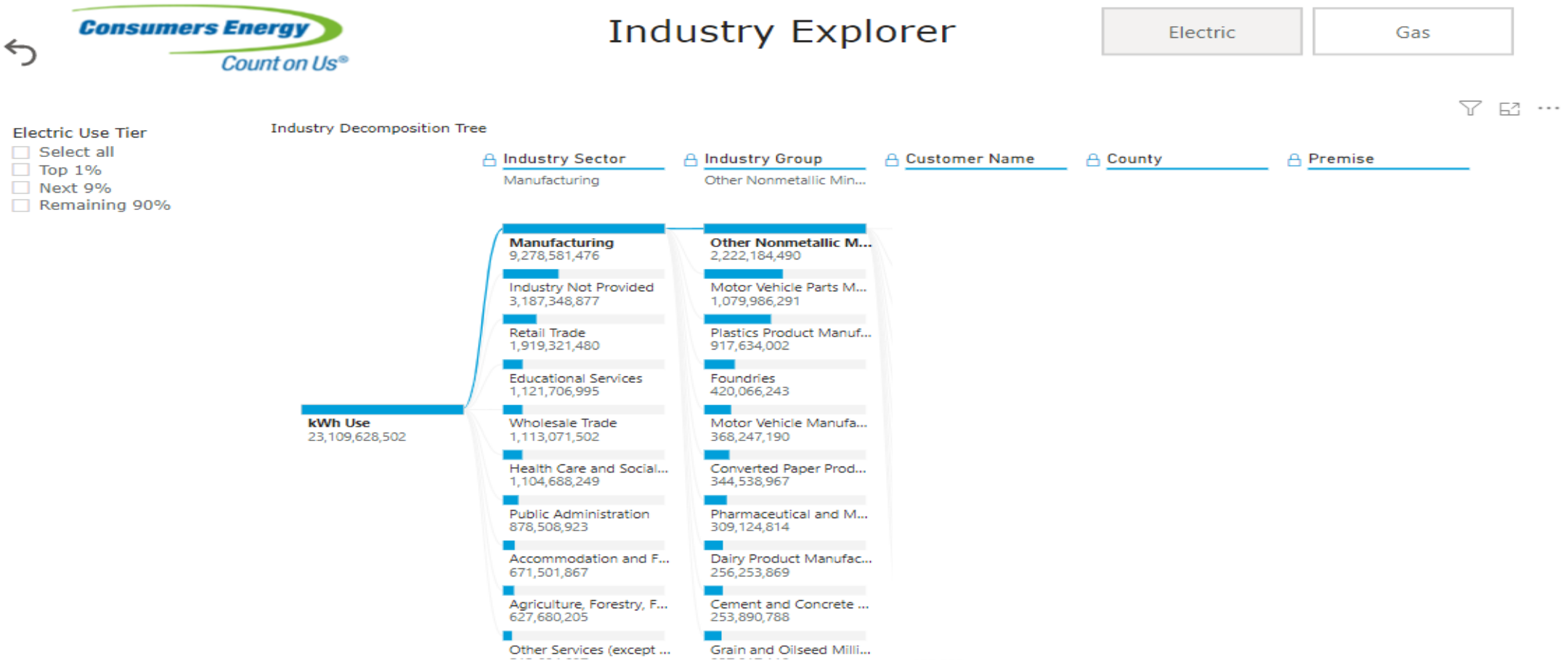
Energy Use by ZIP

Electric | Gas



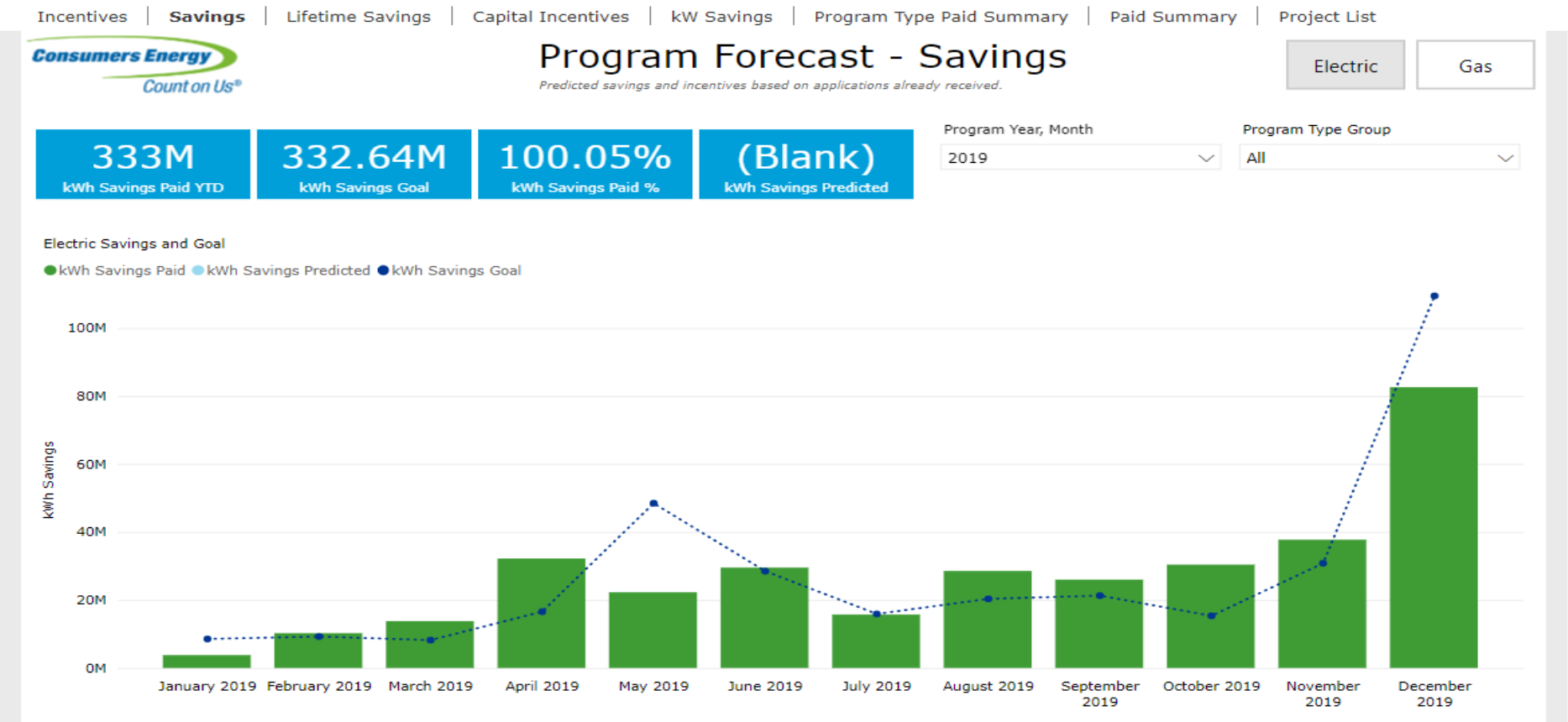
Service ZIP	2022 kWh Savings Ratio	kWh Use	Customers	Accounts
48626	0.0%	1,909,305,091	228	326
49512	1.1%	923,831,651	1,427	2,335
49503	0.5%	540,772,247	1,421	2,691
49037	0.2%	503,154,736	679	1,075
49001	0.7%	503,058,643	763	1,479
49007	1.3%	453,828,316	659	1,474
48640	0.6%	370,837,726	1,258	2,307
48601	0.6%	369,073,604	975	1,898
49221	0.5%	323,979,567	1,299	2,012
48706	0.9%	277,942,067	919	1,668
49548	0.4%	265,394,258	1,281	2,176
49014	0.7%	252,387,757	759	1,203
49720	0.0%	242,616,174	20	30
49442	1.0%	242,047,478	975	1,560
49441	0.4%	240,341,689	1,044	1,770
48507	1.2%	229,248,737	1,337	2,570
49201	0.8%	227,879,274	1,607	2,755
49224	1.1%	227,548,290	496	843
48858	1.0%	225,791,893	1,388	2,808
49002	0.6%	222,463,395	993	1,848
49738	0.1%	215,744,147	432	689
49509	0.4%	212,766,600	716	1,290
49601	0.8%	206,234,091	1,190	2,056
49504	1.3%	201,887,089	862	1,495
48838	0.4%	198,558,809	852	1,314
49461	1.0%	191,953,305	421	614
49634	2.9%	190,606,919	9	13
49203	1.9%	189,383,094	932	1,809
49431	0.3%	180,517,779	935	1,613
49048	1.9%	180,227,913	782	1,460
49544	0.4%	177,467,056	629	939
Total	**0.8%**	**23,109,628,502**	**120,814**	**239,041**

Drilling down from the macro to the micro



Personalized energy optimization recommendations

Data models to close the gap to goal



Questions

Thank you!

For further information, please contact Claude Godin

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