



DATA INTEGRATION FOR UTILITIES AND ENERGY

APPA INSTITUTE FOR FACILITIES MANAGEMENT NEW ORLEANS, LA JANUARY 10, 2024



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Questions related to specific materials, methods, and services will be addressed at the conclusion of this presentation.

PURPOSE OF TODAY'S PRESENTATION

• To provide a broad understanding of:

- Data Warehouses/Data Marts
- How to collect the data
- How to convert data into information
- Examples

WORDS OF WISDOM



If you torture the data enough, it will confess to anything.

DISCUSSION

- Create a report of energy consumption and cost for each building owned by your institution:
 - If served by a District Energy System or local system(s):
 - Chilled Water
 - Steam or Hot Water
 - Electricity
 - Water
 - Fuel-Gas/Oil/Coal
 - If served by the local utility
 - Electricity
 - Fuel-Gas/Oil/Coal
 - Water
 - This year versus last year information:
 - Consumption and cost
 - Hours used and weekly schedule
 - Average number of occupants, i.e. staff, students, faculty
 - Square footage of building including classification(s), i.e. instructional space, administrative, research, housing, etc.
 - Departmental ownership
 - Weather, e.g. average temperatures, % sun, etc.
 - HVAC system type

WHERE WOULD YOU GET THE INFORMATION TO PRODUCE THIS REPORT?

	Table 1: Bu	ilding Summary			
	Buile	ding Data			
Weather Zone	Newark, NJ	Building Name	NJ Office Buildi		
City	Secaucus	Zip Code	07094		
Year Built	1985	Floor Area (sq.ft.)	130,000		
No. of Employees	390	Number of PCs	390		
Weekly Operating Hours	50	Months Used	12		
Percentage Heated	100%	Percentage Cooled	100%		
Data End Point Electricity Usage (kWh) Network Con University	4/30/2012 2,904,251	Total Cost (\$) Electricity Cost (\$) Network Cost (\$)	\$471,289.89 \$402,142.67		
Electricity Usage (kWh)	2,904,251	Electricity Cost (\$)	\$402,142.67		
Fuel Oil Usage (gal)	N/A	Fuel Oil Cost (\$)	N/A		
	Ener	rgy Usage			
EPA Score	39	Electric Usage (kWh/sq.ft.)	22.3		
Natural Gas Usage (kBtu/sq.ft.)	39.5	Weather Adjusted Natural Gas Usage (Btu/sq.ft./HDD)	10.6		
Site Energy (kBtu/sq.ft.)	115.8	Source Energy (kBtu/sq.ft.)	296.0		
Carbon Emissions	Environmenta	l Impact Indicators			
Last Year Natural Gas MtCO3e (tons)	273.5	Last Year Total MtCO2e (tons)	1,676.		
Last Year Electricity	1,403.2	Efficiency Savings Over Previo	ous 220.7		





GROUP DISCUSSION

- What are our FM functions?
- What data is collected by other functions in your organization that you can/want to use?
- What data is collected institutionally that can be used to meet your needs?
- What formats does the data require, i.e. spreadsheet, dashboard, formal reports, etc.?
- Can you currently convert the data into information in the required format(s)? How?

THE DATA PROBLEM



THE PEOPLE PROBLEM





ADDING VALUE TO DATA

How do you get there?

Best Practices in Data Management Five Elements for Success







Platform Common Services





INTEGRATE THE DATA

Data Warehouse operates on an enterprise level and contains all data used for reporting and analysis, while **Data Mart** is used by a specific business department and is focused on a specific subject (business area).

- Aggregate data into a single centralized repository available to all authorized stakeholders
- Integrate the data into consistent subject categories based on how users refer to them
- Apply consistent value representation, units, and descriptors to the data

DATA WAREHOUSE/DATA MART ARCHITECTURE



MINE THE DATA

Data mining is the *non-trivial* process of identifying

- valid
- novel
- potentially useful

and ultimately *understandable patterns* in data.

Data Mining Process



DATA MINING TECHNIQUES

Classification

The process uses predefined classes to assign to objects such as "dog", "cat", "hat", etc. These classes describe the characteristics of items or represent what the data points have in common with each other. This data mining technique allows the underlying data to be more neatly categorized and summarized across similar features or product lines.

• Clustering

Like classification, clustering identifies similarities between objects, then groups those items based on what makes them different from other items. While classification may result in groups such as "shampoo," "conditioner," "soap," and "toothpaste," clustering may identify groups such as "hair care" and "dental health."

• Regression

A statistical method that attempts to create a mathematical relationship between one dependent variable and a series of other variables (known as independent variables).

Association

A simple correlation between two or more items, often of the same type to identify patterns. For example, when tracking people's buying habits, you might identify that a customer always buys cream when they buy strawberries, and therefore suggest that the next time that they buy strawberries they might also want to buy cream.

DATA MINING TECHNIQUES

• Prediction

Prediction involves analyzing trends, classification, pattern matching, and relationships. By analyzing past events or instances, you can make a prediction about an event.

Sequential patterns

Often used over longer-term data, sequential patterns are a useful method for identifying trends, or regular occurrences of similar events. For example, with customer data you can identify that customers buy a particular collection of products together at different times of the year. In a shopping basket application, you can use this information to automatically suggest that certain items be added to a basket based on their frequency and past purchasing history.

Decision trees

Related to most of the other techniques (primarily classification and prediction), the decision tree can be used either as a part of the selection criteria, or to support the use and selection of specific data within the overall structure. Within the decision tree, you start with a simple question that has two (or sometimes more) answers. Each answer leads to a further question to help classify or identify the data so that it can be categorized, or so that a prediction can be made based on each answer.



HOW IS MACHINE LEARNING RELEVANT TO FACILITIES MANAGEMENT?

Predicting Problems

When a facility manager tracks operations with machine learning, the disruptions in normal patterns are just as relevant as the consistencies. For example, if a process suddenly fails to meet its routine performance levels, it's possible to isolate and replace a failing part — before it becomes a problem. Smart technology can be programmed to set alerts when the facility displays inconsistencies, all through self-monitoring data collection.

Tracking Usage

By establishing operational patterns, it's easy for facilities managers to develop proactive system scheduling: parts ordering, cleaning, routine shutdowns, and equipment replacement can all be arranged at the most cost-effective and efficient times.

HOW IS MACHINE LEARNING RELEVANT TO FACILITIES MANAGEMENT?

Optimizing Energy Efficiency

A recent study _investigated deep learning for asset optimization throughout a regular office building. The vast system of sensors tracked 35,000 measured data points per minute and drew insights on everything from prioritized elevator scheduling to kitchen odors, automated temperature adjustments, and lighting controls.

While this project proves an elaborate example, smart tech systems can outpace static programs in balancing building load. For example, most usage — even in HVAC and lighting alone — goes beyond the binary weekday/weekend or workday/holiday schedule. Weather events, holidays, and even major sporting events routinely alter attendance levels, and a smart system can mine historical performance data and respond accordingly.

Savvy Storage

In addition to predicting patterns for real-time applications, machine learning tech can also help to sort, prepare, and store data — suddenly, all this information can be significantly more useful to a manager.

For example, a tech can automatically group and sort data according to time of year, a particular machine performance, or even a type of maintenance. These analyzed, categorized data sets prepare the foundation for smart, organized action.

CONVERT DATA TO INFORMATION

- Microsoft Office
- Third party reporting tools and applications
- Analytics, AI
- Web applications

Knowing that a tomato is a fruit? That's Data.

Knowing not to put one in a fruit salad? That's Knowledge.

EXAMPLE APPLICATIONS

- Convert INFORMATION into KNOWLEDGE
 - Energy Management
 - Operational and Decision Support
 - Maintenance Management
 - Analytics, AI, Fault Detection
 - Reporting

ASHRAE- Great Energy Predictor III- A Machine Learning Case Study

The competition focused on predicting the energy savings of a retrofit in the measurement and verification (M&V) process. Assessing the value of energy efficiency improvements can be challenging as there's no way to know how much energy a building would have used without the improvements.

Competitors were challenged to build counterfactual models across four energy types based on historic usage rates and observed weather. The dataset includes three years of hourly meter readings from over one thousand buildings, extensive characterization of the various buildings, and comprehensive weather data at over a 1,000 different sites around the world.





Energy Report Writer





Month

Hour

Day

MonthYr

Occupancy

Weekday

Daytype

Holiday

5degBin

TempRng

(All)

(All)

(All)

Occ

(All)

(All)

(All)

(All)

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Total

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242.23

218.94

244.64

266.78

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Year	2008	-
Month	(All)	-
MonthYr	(All)	-
Hour	(All)	-
Occupancy	Occ	-
Weekday	(All)	-
Daytype	(All)	-
Day	(All)	-
Holiday	(All)	-
5degBin	(All)	-
TempRng	(All)	-

25

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35 36 37

36		Avg ChW1_	_Tons]					Avg ChW1	_Tons	
37		OSA1_DB		Total]					OSA1_DB		-
38			93.61581458	169.85							94.801150)45
39			93.4403	159.36							94.178804	101
40			93.41629938	161.52							94.084290)39
41			93.25277817	152.55							93.975395	586
42			92.94974775	161.15							93.778901	26
43			92.78548108	169.57							93.706094	417
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Operational and Decision Support

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Forecast for								HRSG #1						Free S	tm										
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Hour	Temperature	Forecast, PPH	Forecast, TH	ABS	CUP ABS	S #2	#1	Output	Boiler	Boiler	#1	#2	#3	UNMH	STEAM	ABS	ABS	#2	#2	#3	#1	#1	OPERATIN	IG CO	DST
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1:00	39	44,688	1,265	10,052	OOS	ON	ON	100%	OFF	OOS	OFF	OFF	OFF	0	-	558	OOS	ON	OFF	OFF	OFF	OFF	Electric	\$	9,017
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4:00	32	8()	<u> </u>	C		ON	ON	100%	OFF	OOS	OFF	OFF	OFF	0	1,172	OFF	OOS	ON	OFF	OFF	OFF	OFF	CHW	\$	8,239
5:00	31	78,445	1,123	OFF	OOS		ON	100%	ON	OOS	OFF	OFF	OFF	0	-	OFF	OOS	ON	OFF	OFF	OFF	OFF	Electric-GTG	\$	27,660
6:00	32	55,813	1,207	OFF	OOS		ON		ON	OOS	OFF	OFF	OFF	0	-	OFF	OOS	ON	OFF	OFF	OFF	OFF			
7:00	35	65,034	1,368	OFF	OOS	VIV				oos	OFF	OFF	OFF	0	-	OFF	OOS	ON	OFF	OFF	OFF	OFF	NET INCOME	\$	31,661
8:00	40	47,352	1,464	7,388	OOS	ON				5	OFF	OFF	OFF	0	-	410	OOS	ON	OFF	OFF	OFF	OFF			
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10:00	52	LOZO	5 1,532	14,998	OOS		Di	cnat	tok		OFF	OFF	OFF	0	-		OOS	ON	OFF	OFF	OFF	OFF			
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21:00	49	45,265	1,484	9,475	005	ON	ON	100%	OFF	005	OFF	OFF	OFF	0	-	526	005	ON	OFF	OFF	OFF	OFF			
22:00	47	49,263	1,475	OFF	005	ON	ON	100%	OFF	005	OFF	OFF	OFF	0	5,477	OFF	005	ON	OFF	OFF	OFF	OFF			
23:00	45	51,940	1,380	OFF	005	ON	ON	100%	OFF	005	OFF	OFF	OFF	0	2,800	OFF	005	ON	OFF	OFF	OFF	OFF			

ANALYTICS FAULT DETECTION AND DIAGNOSTICS



Operational and Decision Support



Operational and Decision Support

	Remove Classification Tab Filter			ENERGY FACTORS							
				Ton-hrs/sq.ftyr	Total Tons	Sq.ft/ton	KWh/sq.ft-yr	lbs/sq.ft-yr	Total NSF		
				3.45	8428.60	834.27	12.00	133.367	5,405,913		
Buildir	Description	•	Year & AVG	CHW-Ton/hrs	CHW MAX Tons	CHW sq.ft/ton	ELE- KWH	STM- klbs	NSF		
0002	ENGINEERING AND SCIENCE COMPUTER POD		2012						6,550.00		
0002	ENGINEERING AND SCIENCE COMPUTER POD		2013								
0002	ENGINEERING AND SCIENCE COMPUTER POD		2014								
0002	ENGINEERING AND SCIENCESCON BUILDING DATA		2015								
0002	ENGINEERING AND SC CE (IPU R P(2016								
0004	ELIZABETH WATERS CENTER FOR DANCE AT CARLISLE GYMN	M	2012				174,353.80	1,171.20	34,805.00		
0004	ELIZABETH WATERS CENTER FOR DANCE AT CARLISLE GYM	1	2013				179,128.00	1219.087			
0004	ELIZABETH WATERS CENTER FOR DANCE AT CARLISLE GYMN	<u>Mr.</u>	· · ·				184,546.00	936.28			
0004	ELIZABETH WATERS CENTER FOR DANCE AT CARLISLE GYMNASI	U	_				186,785.00	900.057			
0004	ELIZABETH WATERS CENTER FOR DANCE AT CARLISLE GYMNAS						169,471.00	238.801			
8000	BANDELIER HALL EAST	Ene	rgy	43331	33	25 787879	7 ,289, 345 ,00	1 1 7 3 .973	8,510.00		
8000	BANDELIER HALL EAST			55	36	230.3888889	L V C W261 D. d	llasteg			
0008	BANDELIER HALL EAST	Utiliza	ation	.4	3.	26. 75	280,657.00	191.874			
8000	BANDELIER HALL EAST			JJ345	29	29 182759	C 129726109	nn#i2741n			
0008	BANDELIER HALL EAST	Indi	ces	37064	32	265.9375					
0009	MARRON HALL						78,516.00	583.356	19,405.00		
0009	MARRON HALL						66,610.00	653.845			
0009	MARRON HALL		41ر				78,516.00	557.522			
0009	MARRON HALL Energy Consumption		2015				75,180.00	970.978			
0009	MARRON HALL		2016				73,093.00	780.885			
0010	SCHOLES HALL		2012	101882	68	649.5441176	389,748.00	1247.431	44,169.00		
0010	SCHOLES HALL		2013	103824	74	596.8783784	407,988.00	1308.659			
0010	SCHOLES HALL		2014	92628	62	712.4032258	406,453.00	1140.447			
0010	SCHOLES HALL		2015	89806	64	690.140625	417,925.00	1097.96			
0010	SCHOLES HALL		2016	86217	63	701.0952381	416,451.00	1017.526			
0011	ANTHROPOLOGY		2012	852519	156	325.8461538	882,871.00	1560.07	50,832.00		
0011	ANTHROPOLOGY		2013	771147	124	409.9354839	785,637.00	1848.33			



Network Plot 🛛 🗖 🗖 🗙

Move legend.

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QUESTIONS & ANSWERS Thank You!



THIS CONCLUDES THE AMERICAN INSTITUTE OF ARCHITECTS CONTINUING EDUCATION SYSTEMS COURSE

