



TESCO METERING

You Went AMI: Where Will You Go Next?

Metering Analytics and AI in Meter Shop Operations



Mid South Electric Metering Association 73rd Meter School

Wednesday May 7, 2025 Group 3: 8:00 AM Tom Lawton

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TOPICS TO COVER

You have gone AMI. Where do we go from here?

Reads are coming in. Meters are working. Coverage is good. Starting to make use of the data. What is next?

In this presentation we will look at many of the new opportunities and technologies we have available to us as well as some of the new challenges that we will be facing in coming years.

- AMI 2.0
- Improving Communications and reliability of our AMI coverage
- Operational Challenges in the future
- Artificial Intelligence what AI is and how we are starting to use this new tool





SETTING THE STAGE - THE PROMISE OF AMI

The introduction in 2007 of mass deployed Advanced Meter Infrastructure (AMI) systems promised more effective and more efficient Meter Service Operations.

This was to be accomplished in a variety of ways starting with:

- No need to manually read meters (if AMR had not previously been deployed)
- No need to roll a truck to perform a disconnect or a reconnect
- Better ability to detect and respond to outages
- Better ability to detect theft
- Better ability to detect (and eventually capture) unbilled energy
- Better understand customer usage and make better energy buying decisions

And with all of this came a promise of "Additional Capabilities and additional Operating data."



WHERE WE ARE NOW

We are over 85% deployed in the US and Canada and Electric Utilities now collect hundreds of millions of events and readings every day from sources such as the following:

- Meters (status, manufacturer, purchase date, events such as reprogramming notifications and tamper alerts)
- Transformers (ID, circuit section, circuit ID)
- Service points
- Customer accounts (type, status, billing cycle)

Utilities and meter manufacturers have been developing, using and improving a variety of alarms, notifications and reporting on this data and have been reaping operational benefits.





MOVING INTO THE FUTURE AMI 2.0

AMI 2.0 is being rolled out. The basic concept is to move more of the data filtering/analysis to the meter so that less information is sent and what is sent is more worthwhile.

Better Analytics are being developed by Utilities, Meter Manufacturers and a variety of third parties both inside and outside of the metering space.

Artificial Intelligence is starting to become a viable business tool to assist in taking these analytic capabilities to the next level.



AMI 2.0



Can we use our existing infrastructure?

Do we have to rip out and replace with a new infrastructure?

What about LTL back haul or a Private Network?

What about Power Line Carrier? Is there life there for my most remote service areas?



New Tools



 Advanced visualization tools – Built-in tools provide an alternative to cumbersome data tables and provide enhanced visibility of your smart meters, AMI network, and distribution network

 AMI system health dashboards – A custom definable user interface enabling a visualization of real-time events and trending





2025 and Beyond (cont.)

Residential loads will move further and further away from power factors of one and put increasing pressure to move to either a Blondel solution for them, a VA/VAR solution for them, or a correction factor for them as AMI systems begin to report back customer power factor for all metering solutions

- 12S or 2S?
- kVA/kVAR or kWh w/ PF correction?
- DC metering?





2025 and beyond (cont.)

On the distribution side customers are already being encouraged to put in more and more renewable energy and they will also add more and more energy storage. New DER's are popping up every day.

- Larger customer-based energy production and solutions will lead to expanded micro grids.
- Second Generation AMI and potentially new communication paradigms as LTL data becomes less and less expensive and reaches larger and larger areas. This will become essential as we try to manage these new DER's.





Generation vs Storage



Utility grade energy storage will replace new generation at an increasing pace as some of the largest capital investment projects for utilities.

The great tunnel under Niagara Falls, Ontario \$1.6 Billion; 150 megawatts – part of an Ontario plan to shut all their Coal generation Plants



New generation projects are increasingly becoming renewables coupled with energy storage Island communities are already showing us this on larger and larger scales – *Ta'u American Samoa; 1.5 megawatts with battery storage for three days*



AMI 2.0 Infrastructure

- Second Generation AMI and potentially new communication paradigms as LTL data becomes less and less expensive and reaches larger and larger areas – without new infrastructure
- Research in Power Line Carrier Technology may provide expanded bandwidth to allow for greater data transfer more frequently without as much new infrastructure
- Mesh networks continue to improve and AMI 2.0 is anticipating leveraging the infrastructure installed in AMI 1.0





Artificial Intelligence is quickly moving from novelty to essential for business operations.

Al is starting to be used in Metering Operations as well as in other parts of Utility Operations. Coupling Al with ever-improving Meter Analytics is allowing us to take greater advantage of the copious data generated by AMI and AMI 2.0.

For the balance of this presentation we will discuss:

- What AI is
- The various platforms that exist
- How AI is intended to be used
- What AI is not
- Case studies in how we are already using AI to improve our distribution system, reduce costs and help the customer





Artificial Intelligence (AI)

The Field of Computer Science that seeks to create intelligent machines that can replicate or exceed human intelligence



BRIEF HISTORY OF AI

rief history of Al		
Artificial Intelligence Machine Learning	-00 1956	Artificial Intelligence The field of computer science that seeks to create intelligent machines that can replicate or exceed human intelligence.
Deep Learning	0 0 1997	Machine Learning Subset of AI that enables machines to learn from existing data and improve upon that data to make decisions or predictions.
	2017	Deep Learning A machine learning technique in which layers of neural networks are used to process data and make decisions.
Generative AI	2021	Generative AI Create new written, visual, and auditory content given prompts or existing data.





Foundations of Al

Standard Statistical Techniques and Methods



STATISTICS: PROBABILITY THEORY



 $P(A) = \frac{\# \text{ outcomes in event } A}{\text{total } \# \text{ of outcomes}}$

Probability Theory deals with the uncertainty and likelihood of events

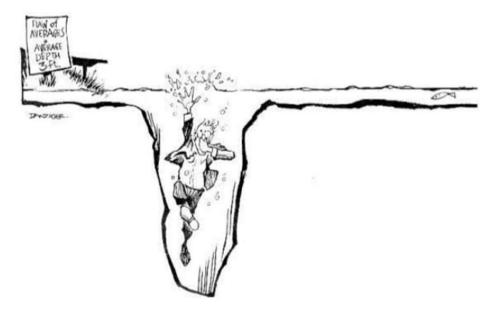
Utilized in predictive modeling where AI systems determine the likelihood of events – think speech recognition or predictive text



DECISIONS AND PREDICTIONS

Flaw of Averages

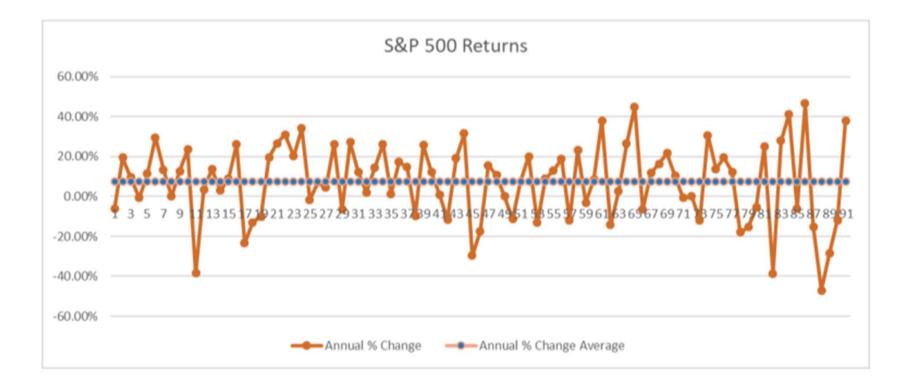
"Never try to walk across a river just because it has an average depth of four feet." —Milton Friedman



https://web.stanford.edu/~savage/faculty/savage/FOA%20Index.htm



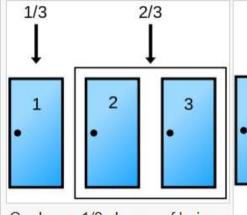
RANDOMNESS AND CHANCE



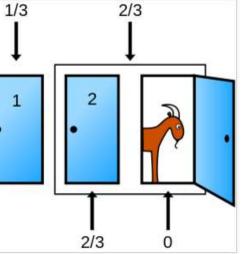


MONTY HALL





Car has a 1/3 chance of being behind the player's pick and a 2/3 chance of being behind one of the other two doors.

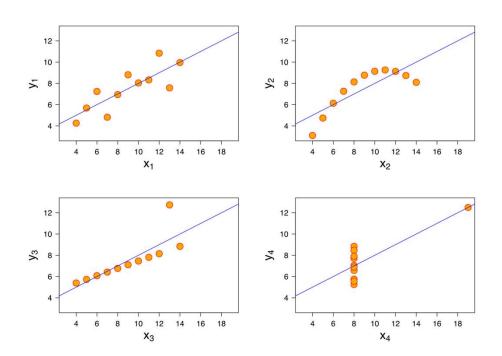


The host opens a door, the odds for the two sets don't change but the odds move to 0 for the open door and 2/3 closed door.

STATISTICS: LINEAR REGRESSION

Linear Regression is a method to model relationships between variables.

Used to supervise learning to predict outcomes.



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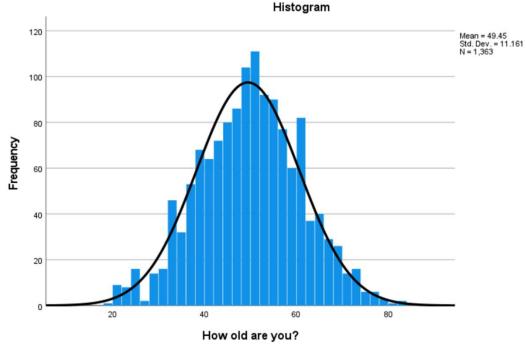
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STATISTICS: STATISTICAL INFERENCE

Statistical Inference is

the process of using data analysis to infer properties of an underlying probability distribution

Allows for conclusions to be drawn about a population based on sample data



By Psychstudent25 - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=117711252

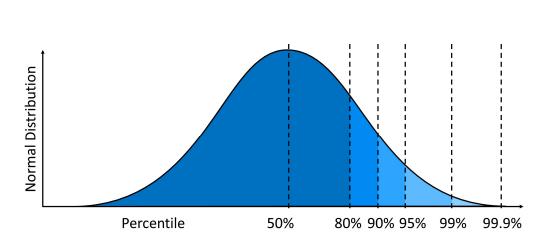


STATISTICS: HYPOTHESIS TESTING

Hypothesis testing

validates assumptions made about data through tests like T-tests or ANOVA.

Ensures the reliability and accuracy of models during training.



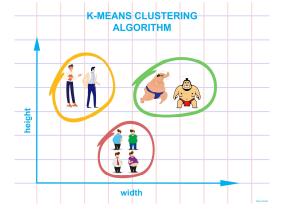


STATISTICS: CLUSTERING AND CLASSIFICATION

Clustering and classification

groups data (clustering) or assigns it to predefined categories (classification)

Techniques used in unsupervised or supervised learning such as Kmeans (clustering) or Decision Trees (classification)



A Friendly Introduction to K-Means clustering algorithm | by Tarlan Ahadli | Medium

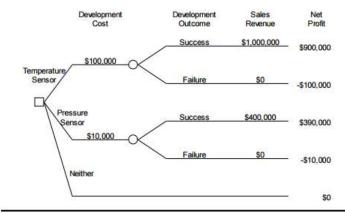


Figure 1.1 Special Instrument Products decision

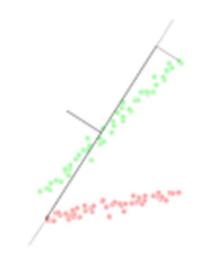


STATISTICS: DIMENSIONALITY REDUCTION

Dimensionality Reduction

reduces the number of variables in datasets.

Reducing features aids in enhancing computational efficiency as well as reduces noise

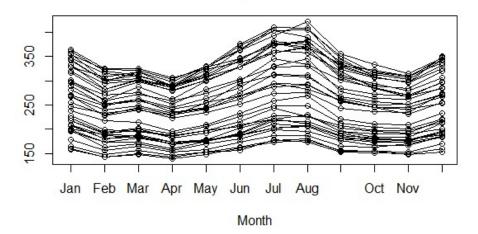


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STATISTICS: TIME SERIES ANALYSIS

Time Series Analysis analyzes data points ordered in time to forecast future trends – think weather forecasting or seasonal electricity usage Seasonal plot: usmelec



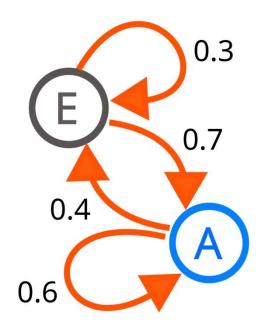
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STATISTICS: MARKOV CHAINS

Markov Chains model sequences of events where each event depends only on the previous event

Foundational for NLP (natural language processing) and reinforcement learning



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STATISTICS: MARKOV CHAINS

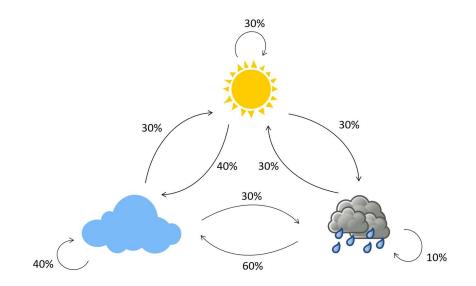
An example of a Markov Chain

Consider a simple weather model with three states:

- 1. Sunny (S)
- 2. Cloudy (C)
- 3. Rainy (R)

A transition matrix for the weather might look like this:

- If it's Sunny, there is a 30% chance it stays Sunny,
 40% chance it becomes Cloudy, and 30% chance it rains the next day.
- If it's Cloudy, there is a 30% chance of Sun, 40% chance it stays Cloudy, and 30% chance of Rain.
- If it's Rainy, there's a 30% chance of Sun, 60% chance of Cloudy, and 10% chance it stays Rainy.







Foundations of Al

Analytics, Data Engineering & Data Science, Machine Learning

ANALYTICS



The process of analyzing data to discover useful insights, patterns, and trends to help make informed decisions.

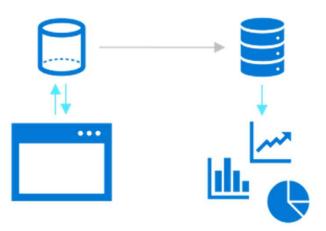
- Descriptive Summarize historic data
- Diagnostic Understand why something happened by delving deeper into data
- Predictive Use data, machine learning, and/or statistical techniques to predict future events
- Prescriptive Recommendations for decision-making by suggesting the best course of action based on data





DATA ENGINEERING AND DATA SCIENCE

- Data Engineering
 - Structure, semi-structure, unstructured data
 - Integration, consolidation, cleansing, transformation
 - Operational and analytical data, streaming data, live data
 - Data pipelines, data lakes, data warehouses





DATA ENGINEERING AND DATA SCIENCE

Feature	Data Pipeline	Data Lake	Data Warehouse
Purpose	Moves & processes data	Stores raw data	Stores structured, processed data
Data Type	Any type	Raw, unstructured, semi-structured	Structured
Processing	Transforms data	Schema-on-read	Schema-on-write
Use Case	Data movement, ETL/ELT	Big data analytics, ML	Business intelligence, reporting
Storage Format	Temporary or structured	Any format (JSON, CSV, Parquet)	Relational tables (SQL)

How They Work Together

1.Data Pipeline moves data from sources (APIs, IoT, applications) into a **Data Lake**.

2. Analysts explore and prepare data from the Data Lake for deeper insights.

3.Processed & structured data is transferred from the Data Lake to a Data Warehouse for BI and reporting.



MACHINE LEARNING



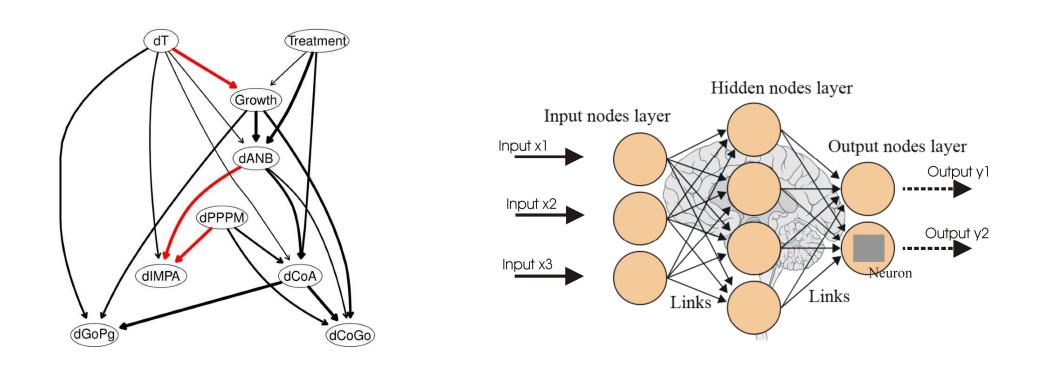
Cloud and Compute
CPU, GPU, Quantum

Machine Learning is a subset of AI that enables machines to learn from existing data and improve upon this data to make decisions or predictions





BAYESIAN AND NEURAL NETWORKS



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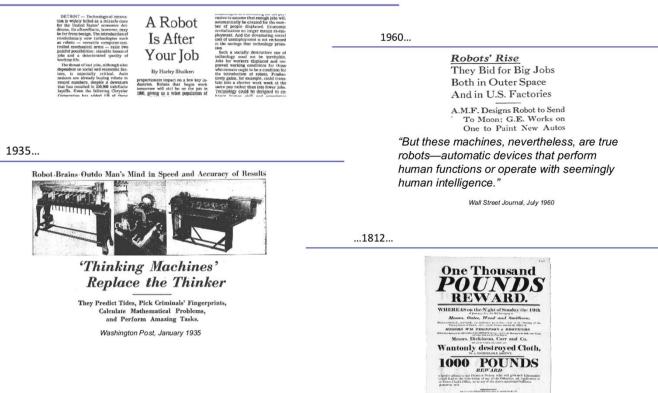
ARTIFICIAL INTELLIGENCE – REPLACING HUMANS?





MISCONCEPTIONS ABOUT TECHNOLOGY & AI OVER TIME

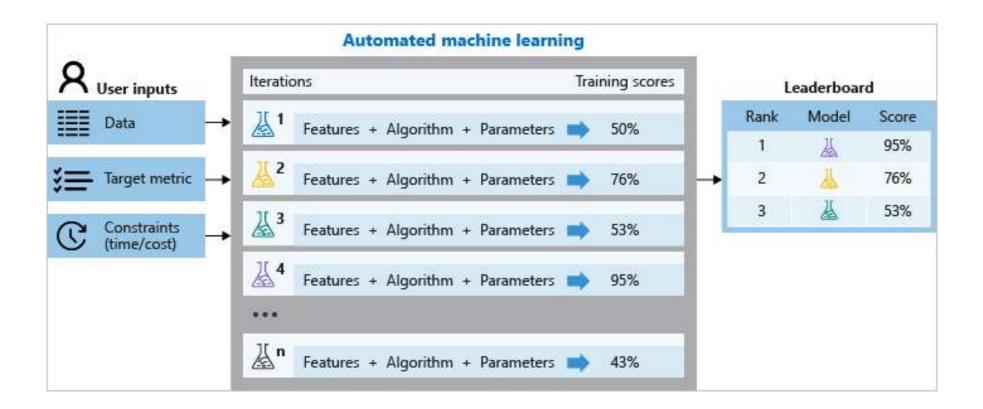
1980...



Reward Poster for Luddite Attacks Near Leeds, March 1812



AUTOMATED MACHINE LEARNING





AI AND CG







Oversized Transformer Reporting

Platforms used:

Meter Manager – has all physical assets at every location including the instrument transformers

Consumption information from the head end – in this case a Silver Spring/Open Way head end





Oversized Transformer Reporting

Output:

A monthly report of the most egregiously oversized transformer installations with usage going back over the past two years to demonstrate and estimate lost revenue

Use:

Field services receives monthly work orders to replace the instrument transformers with appropriately sized transformers. Extended range transformers further improve the effectiveness of the monthly billing





Oversized Transformer Reporting

Results:

A steady increase in monthly revenue gains on every Commercial/Industrial account addressed. Payback for the work is under three months in every case as there are so many oversized accounts.



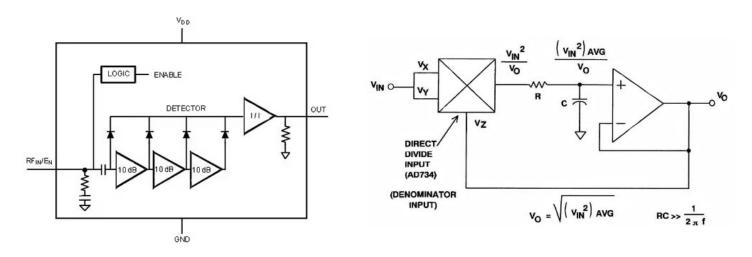


A few case studies on how to use data across platforms

Micro Arc (RF) Detection and Reporting

Platforms used:

Itron Open Way head-end and L+G Gridstream head-end with customized analytic software – receive alarm data on the RF signature of electrical arcs in or around the service.





Micro Arc Detection and Reporting

Output:

A weekly report identifying sites with RF detect (micro arc) alarms that fit an identified pattern. Determine which sites to send a Meter tech with RF detection equipment to detect where the RF signals may be coming from as they typically are not coming from the meter but are coming from relatively close by (with 100 feet).

Use:

Field services inspection involves a visual detection as well as the use of RF detection equipment to pinpoint the source of the problem.





MODEL M331 MINI RFI LOCATOR



Micro Arc Detection and Reporting

Results:

Safety hazards found in the field were initially anticipated to be only failed socket jaw (hot socket) events, but this proved to be only a fraction of what was found. Some of the various safety related issues discovered in the field include;

- Failed meter socket jaw
- Frayed and breaking weather head connections
- Arcing on a customer circuit on the customer side of the service panel in the home
- Arcing at the connection to the Distribution transformers closest to the house and failing Distribution Transformers
- Arcing in the manual disconnect mechanism of the meter box
- Frayed and failing wires between the socket and the service panel in the home





Voltage Optimization

Platforms used and background:

Raw data from metering end points brought back in near real time. This can be accomplished much easier using AMI 2.0 to filter out standard voltage readings that are not an issue and only send back voltage readings that are outside the norm desired or expected.

AMI 2.0 will allow for real time voltage readings across the entire service territory without inundating the head end with data. This data can then be used for Conservation Voltage Reduction (CVR) and Volt/VAR Optimization (VVO) programs. Both can provide significant improvement to the distribution system's performance and reduce cost for the utility.





Voltage Optimization through CVR

Conservation Voltage Reduction:

CVR is a technique where utilities lower distribution voltage to reduce energy consumption without affecting service quality. Using AMI real time AMI data and AI utilities can optimize voltage dynamically instead of simply using a fixed set point. This has proven to reduce energy consumption by 1 to 3% per volt.





Conservation Voltage Reduction (CVR) in action

Pacific Gas & Electric (PG&E)

- Used several thousand metering end points to provide near-real time voltage information at customer end points.
- Deployed Automated Voltage Control systems at substations
- Applied analytics software to continuously adjust voltage based on the real-time meter data
- Coordinated CVR with demand response programs to ensure that voltage adjustments aligned with peak demand reductions

Results:

- Achieved a 1 to 3% reduction in energy demand per volt reduction
- Improved energy efficiency across more than 500 circuits
- Improved customers satisfaction with better power quality and fewer voltage related issues







Voltage Optimization with VVO

The holy grail of Voltage Optimization though is actively managing both the voltage and the reactive power (VVO).

Output and Use:

Using AMI data and AI utilities can feed automated control systems in real time to continuously manage and adjust:

- Voltage regulators to fine tune local voltage levels.
- Capacitor banks to manage reactive power and improve power factor
- Load tap changers (LTC's) in substations to regulate voltage dynamically.





Volt/VAR Optimization (VVO)

Results:

This automated control allows utilities to optimize power flow and reduce line losses. This also allows for **Over Voltage detection and correction** preventing equipment damage and customer complaints as well as **Undervoltage issues** that allow customers to have sufficient voltage to always power their appliances, HVAC systems and other equipment properly and extending their life. The **Phase imbalance corrections** applied to the system this way corrects a host of power quality issues and energy waste due to better power factors through these automated corrections.

This enhancement of grid automation through AMI and AI provides:

- Energy Savings without affecting the customer experience
- Line Loss reduction reducing distribution costs
- Improved Power Quality
- Better DER integration by stabilizing voltage for renewables on the other side of the meter





VVO in action

Duke Energy

- Installed voltage regulators, capacitor banks, and load tap changers (LtC's) at substations
- Used AMI to collect real-time voltage readings from the metering end points
- Integrated the AMI data with a Distribution Management System and an Advanced Distribution Management System to enable dynamic voltage adjustments
- Used machine learning algorithms to predict voltage fluctuations and make preemptive adjustments.

Results:

- 2.5 to 3% reduction in energy consumption without affecting service quality
- Reduced line losses by 1 to 2%. This was worth millions in cost savings annually.
- Improved power quality and reduced vltage related complaints from customers.







Other Utility Analytics

- Transformer Overload
 Identification
- Behind The Meter Identification
- Weather Sensitivity
- Wholesale Settlements
- Mark-to-Market
- Suitability for DER
- Profitability
- Grid Loading
- Demand Forecast
- Generation Forecast
- ISO Forecast

- Net Open Position
- Scenario Analysis
- Coincidence Peaks
- Load Optionality
- Grid Constraints Load Scheduling
- Demand Response
- Risk Management
- Decarbonization
- Cost Reduction
- Customer Engagement
- Billing
- Grid Dispatch & Planning



AI PLATFORMS

Google Gemini











HOW TESCO IS USING AI

Nighthawk platform:

- 1. Doubled productivity of both the software development teams (Meter Manager, TDM, Nighthawk) and the Nighthawk support teams
- 2. Doubled the number of users in one year for Nighthawk and added close to ten million metering assets for Meter Manager
- 3. Rewrote large sections of the Nighthawk platform, wrote Meter Manager 3.0, and released new revisions for TDM in a series of monthly sprints. This ability to move so much faster with the assistance of AI significantly reduced system errors and User errors for all three platforms aka making the applications bulletproof

Better and Faster, with the same budget



Drive flawless execution in your operations





AMI 2.0 INFRASTRUCTURE

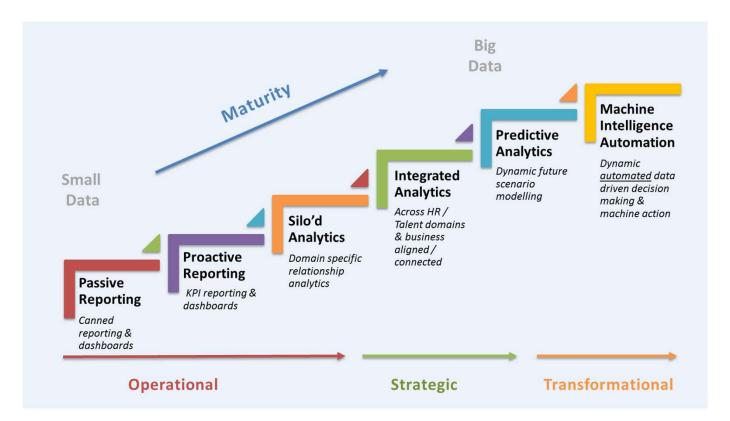
Second Generation AMI and potentially new communication paradigms as LTL data becomes less and less expensive and reaches larger and larger areas – without new infrastructure and by starting to integrate machine learning and AI.

- Research in Power Line Carrier Technology may provide expanded bandwidth to allow for greater data transfer more frequently without as much new infrastructure
- Mesh networks continue to improve and AMI 2.0 is anticipating leveraging the infrastructure installed in AMI 1.0
- The ability to use cellular and fiber to fill in holes in an AMI system or handle remote areas

We can receive real-time data to help fun our distribution systems more effectively and more efficiently using AMI 2.0 and AI



ANALYTICS MATURITY CURVE





QUESTIONS AND DISCUSSION

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This presentation can also be found under Meter Conferences and Schools on the TESCO website: tescometering.com