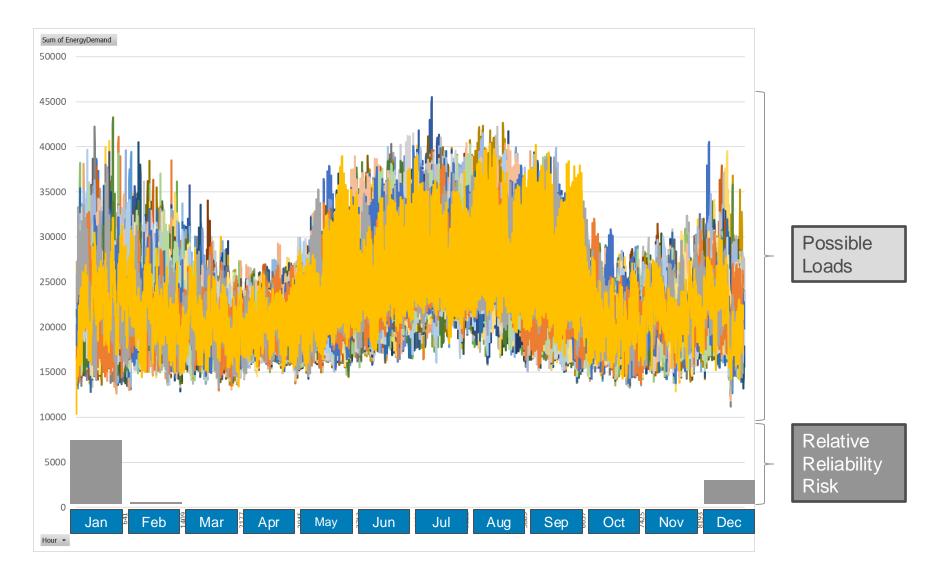


AI, Machine Learning, & Ethical Considerations

John Dirkman, Michael Riesen, Nora Esram, Haider Khan, Brandi Hurst, Kenneth Shiver

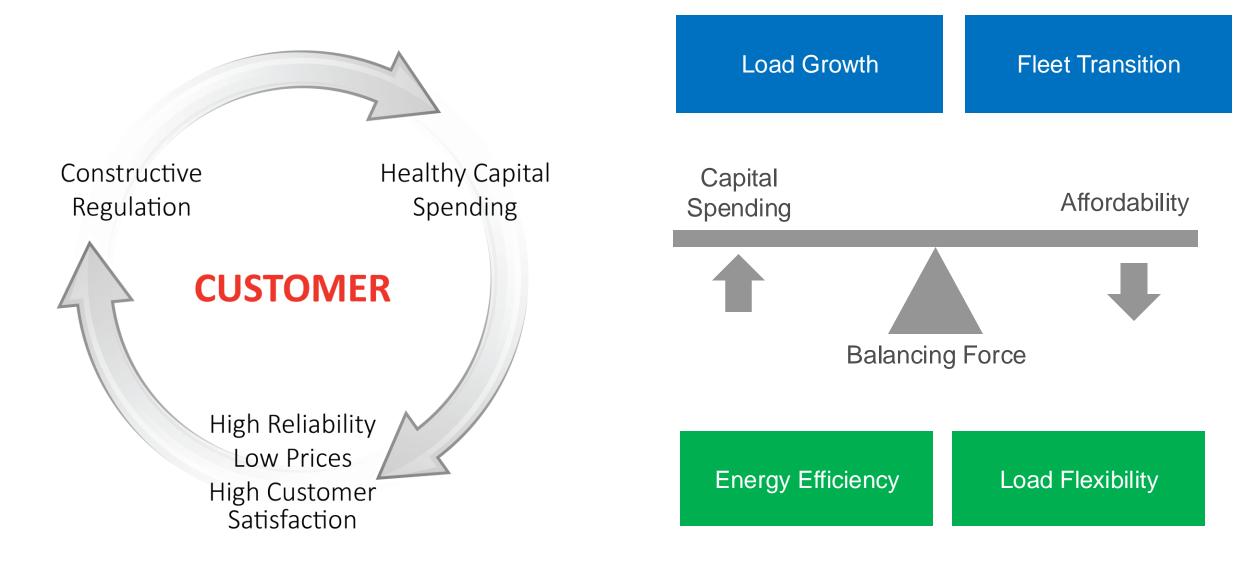
Resource Plan Economics of Energy Efficiency and Demand Response



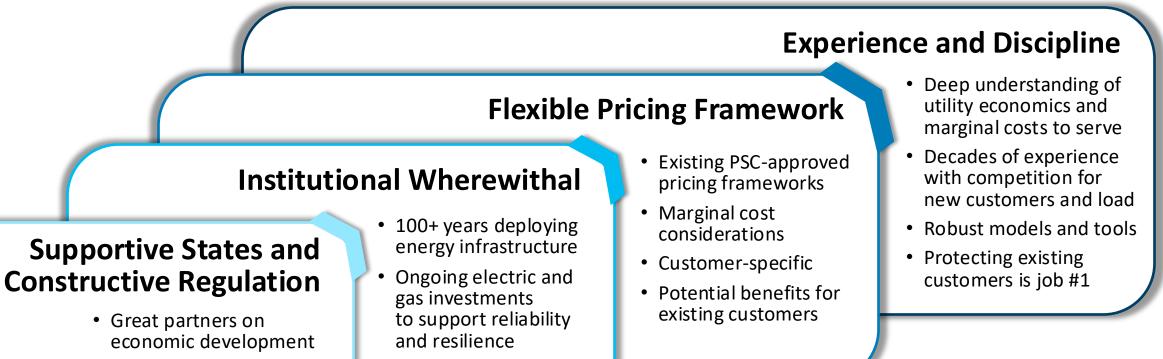


How does DSM relate to Southern's Strategy?





We are well positioned for the growth opportunity...

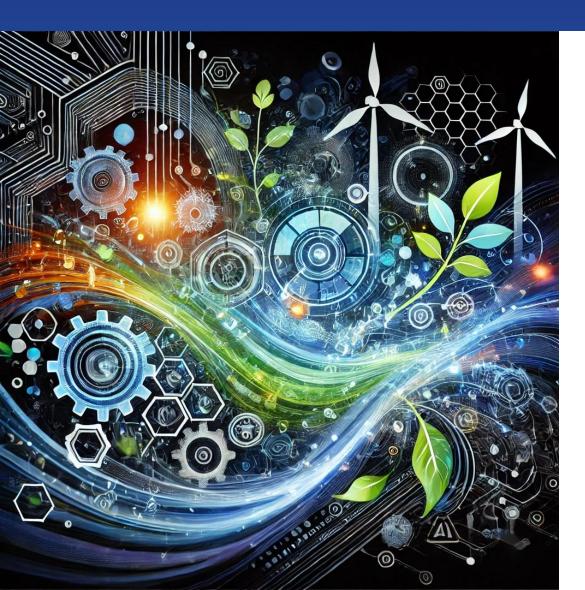


- Policies that promote and support growth
- Focused on reliability and affordability

 Deep experience with every major energy supply technology

Our long-term integrated resource planning processes are the cornerstone of our ability to provide clean, safe, reliable and affordable energy to serve growing needs

What are the basics?



Machine Learning and AI
Models
AI Model Types and Training
Data
LLMs vs. Industry-Specific
Models

Machine Learning and Al Models

- Machine Learning (ML): A subset of AI where systems learn patterns from data to make predictions or decisions without explicit programming.
- Artificial Intelligence (AI): Refers to the broader concept where machines mimic human intelligence, including reasoning, problem-solving, and language understanding.
- **Models:** Mathematical frameworks used to predict outcomes based on training data. In ML, models are trained on historical data to identify trends.
- **Relevance:** What is relevant between input data and the expected output



AI Model Types and Training Data



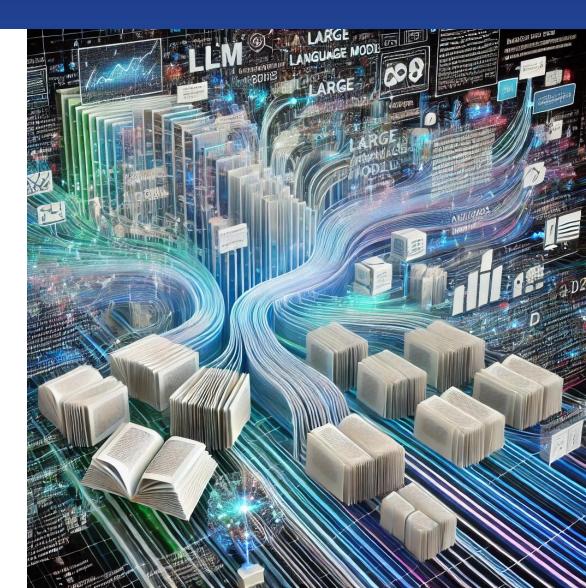
- Supervised Learning: Models trained on labeled data. Example: Predicting energy demand using historical usage patterns and weather data.
- **Unsupervised Learning**: Models find hidden patterns in unlabeled data.

Example: Clustering energy consumption behavior to optimize tariffs.

- Reinforcement Learning: Models improve via trial and error. Example: Smart grid optimization, learning efficient energy distribution strategies.
- **Training Data**: Structured (e.g., smart meter readings) and unstructured (e.g., satellite images tracking infrastructure).

LLMs vs. Industry-Specific Models

- Data Collection: LLMs are trained on massive datasets that include books, articles, websites, and other forms of human language.
- Tokenization/Breaking Down Language: Text data is split into tokens, which are smaller chunks such as words or subwords. The model learns how these tokens relate to each other in context.
- Training: The model learns by predicting missing words in a sentence or the next word in a sequence, reinforcing its ability to understand language patterns.
- Fine-Tuning: LLMs can be fine-tuned on specific tasks, such as legal text analysis, customer support, or medical literature.



LLMs vs. Industry-Specific Models

Dynamic Load Balancing: AI predicts energy demand, enabling realtime load distribution to avoid blackouts and improve grid reliability.

Predictive Maintenance: Machine learning analyzes grid equipment data to forecast failures, reducing downtime and repair costs.

Integration of Renewables: Al optimizes the integration of intermittent renewable energy sources (e.g., solar, wind) into the grid by forecasting availability and demand.

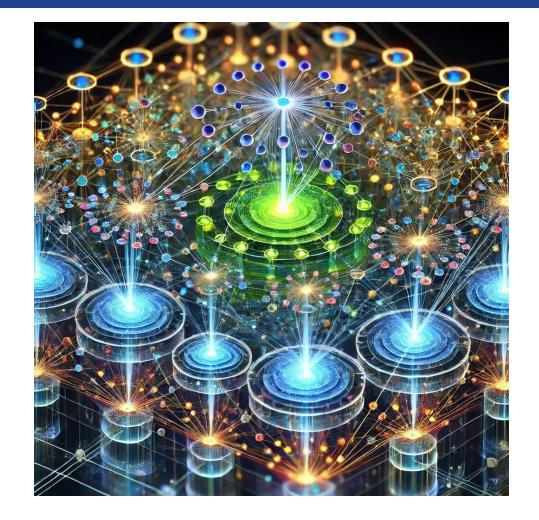
Demand Response: Al allows buildings to adjust energy usage in response to peak demand signals, lowering costs and stress on the grid.

Smart Energy Systems: Al-driven systems automate HVAC, lighting, and power use based on occupancy and environmental data.



LLMs vs. Industry-Specific Models

Poor data quality whether it's biased, incomplete, outdated, or inconsistent—can lead to inaccurate predictions and decisions.



How do we know?

Why is it better?

Legal Considerations



- Legal Implications
 - Regulatory Compliance: AI-driven systems must align with existing environmental laws and energy regulations.
 - Data Privacy: Managing personal and operational data in AI-enhanced systems may raise privacy concerns, requiring robust legal frameworks.
 - –Liability in AI Decisions: As AI systems make more decisions, who is liable in case of failures or inaccuracies?

COMPANY OVERVIEW

SEW

AI-Powered Connected Customer (CX) and Workforce (WX) Experience Industry Cloud Platforms

+ Energy Transformation	+ Water Conservation	+ Energy Efficiency
+ E-mobility	+ Net Zero	+ ESG

SEW AT GLANCE













ABAB ncace. Ucate. mpower.

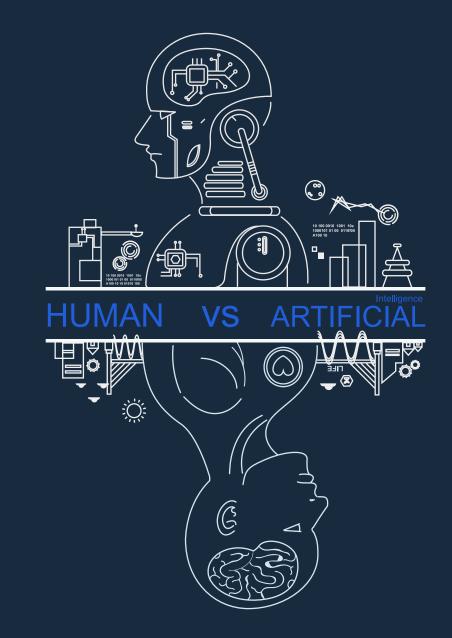
CX Customer Experience Platform

BX Integrated Business Experience Platform

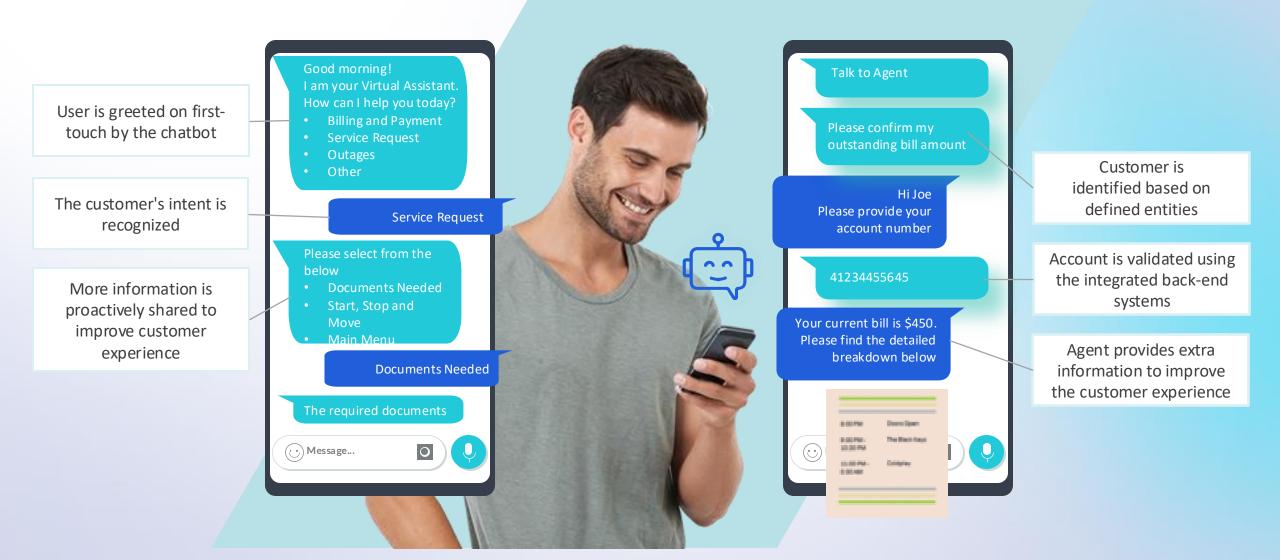
WX Field Workforce Experience Platform

Intelligent Chatbots & Virtual Agents

Humanized AI



Intelligent & Personalized Conversational AI Interactions



ChatBot Business Dashboard / Analytics / Reporting

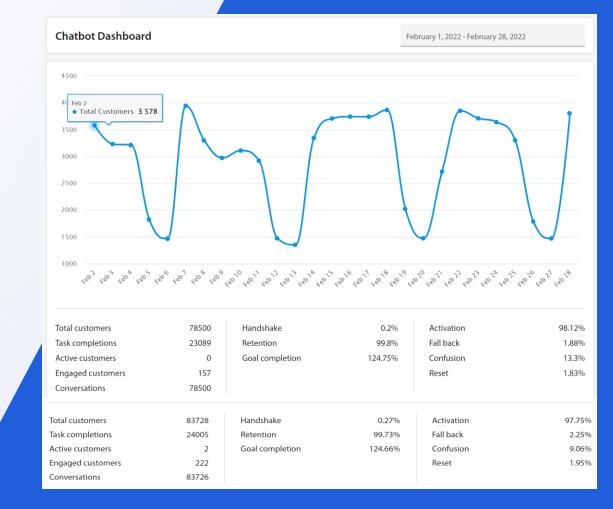
The New, Intelligent, and Modern Customer Service Bot

Business Benefits

- 100% AI Capabilities
- Improved Data Collection
- **40-52%** Reduction in Cost to Serve
- 90% Customer Satisfaction
- Automated Business Operations

Reports and Analytics

- Chatbot Dashboard
 - Total customers
 - Active Customers
 - Engaged Customers
 - AI Conservations
 - Retention Rate
- Chat Details
- Intent Analysis
- Category Tracking
- Keyword Tracking





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Al for a Smarter Grid



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John Dirkman, P.E.

VP, Product Management jdirkman@resource-innovations.com



RI provides clean energy and tech enabled services

Resource Innovations boasts over two decades of expertise in program design, delivery, and grid management software and services, and is powered by a robust team of more than 80 energy engineers.

RI's team of over 800 employees provides a comprehensive range of innovative technologyenabled services, software, and consulting to over 150 electric and gas utility clients across North America and internationally, ensuring a wide breadth of program services that extend from grid operations to the customer level.

No.12

Inc's 2023 Fastest Growing Private Energy Company

800+

Employees

150+ Global Clients

880+

Programs and Projects managed since 2019

825K

Metric Tons of CO2 emissions avoided in 2022



Resource Innovations Utility Software and Services

Software

&

Services

</>

Grid Software

- Grid360 Grid Analytical Engines
- Grid 360 Grid Impact Assessment System
- Reactive Power Coordination System
- Grid Network Model Optimization System
- Financial Transmission Rights Management System
- SPIDER Long-term DER and EV Forecasting
- iEnergy Workflow Management and Customer Engagement Platform
- EV Charging Data Aggregation Platform -Consolidate, Validate, and Analyze CPO data

Grid Security powered by OTORIO

• Asset Visibility

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- Risk Assessment and Management
- Proactive Exposure Discovery
- Audit & Compliance
- SOC and Response Integration
- Penetration Testing and Incident Response
- Secure Remote Access

Grid Modernization

- GT&D Operations and Expansion Planning
- Grid Reliability and Compliance
- Grid Modernization Analysis, Strategy and Support

Customer Strategy

- Portfolio and Program Planning
- Behavioral Science and Research
- Demand Response Strategy
- Fleet Electrification
- System Economics/Locational Resource Planning
- DER Integration

Customer Initiatives

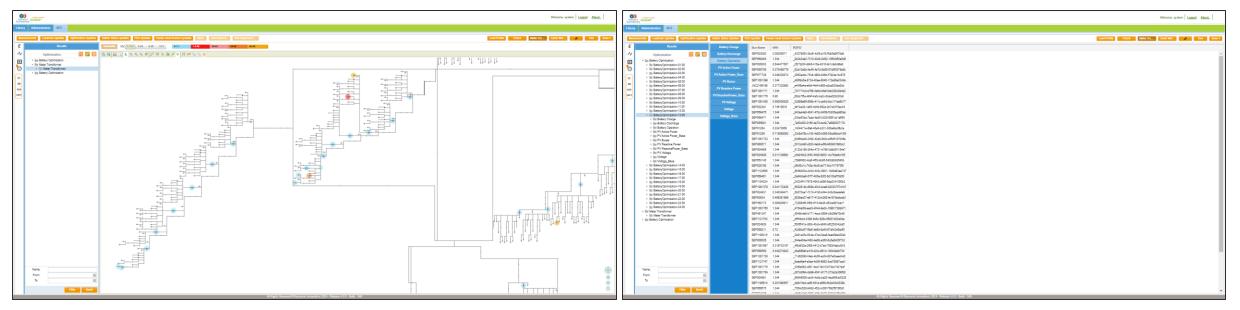
- Program Design
- Program Marketing and Customer Engagement
- Program Implementation and Delivery
- E-Commerce Marketplace
- Regulatory Compliance and Reporting



Al for Data Quality Improvement and Battery Placement DOE, BIRD Foundation, ASU

Application to use AMI data to validate meter to transformer connection to improve distribution network models. Important for accurate voltage drop calculations, outage prediction/management, and transformer loading calculations.

Application to recommend battery placement and charge/discharge times to mitigate voltage and overload problems caused by PV generation.



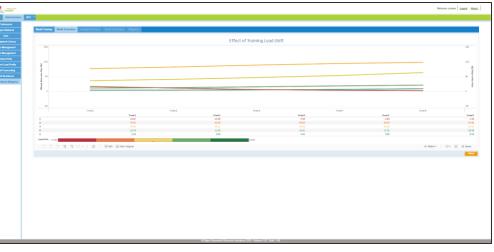
Meter to Transformer Connection

Battery Placement and Charge/Discharge



AI for Detecting and Mitigating Cyberattacks DOE, BIRD Foundation, ASU

Goal: A machine learning-based framework to detect and mitigate cyberattacks that redistribute loads by modifying measurements. The detection framework consists of a multi-output support vector regression (SVR) load predictor and a subsequent support vector machine (SVM) attack detector to determine the existence of load redistribution attacks. The SVM attack detector is trained using normal data and randomly created load redistribution attacks so that it can maximally explore the attack space. The results show that the SVM detector trained using random attacks can effectively detect not only random attacks but also intelligently designed attacks. Moreover, using the SVR predicted loads to re-dispatch generation when attacks are detected significantly mitigates the attack consequences.



Effect of Training Load Shift

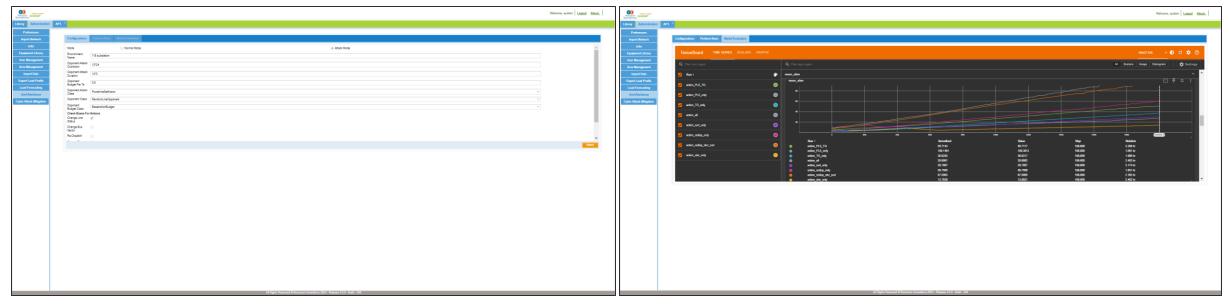






Reinforcement Learning for Improved Resilience DOE, BIRD Foundation, ASU

With complex power grids, the action space for simulating attacks and improving resilience (decreasing line loading) expands exponentially, making it difficult for reinforcement learning (RL) agents to explore and find effective solutions efficiently. The innovative Temporal Graph Convolutional Network (TGCN) framework offers a scalable solution for safeguarding cyber-physical systems against attacks via consideration of various actions: changing substation topologies, changing the state of power line switches, changing the operating schedule of generators, limiting the production of renewable generators, and/or changing battery storage between charging and discharging.



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JURCE INNOVATIONS

24

Al for a Smarter Grid Use Cases

- 1. AI for additional data validation and correction: network model and load data
- 2. Al for load, generation, and price forecasting short-term (hours/days) and long-term (years)
- 3. AI-based advisory tools for grid operators knowledge base
 - a. Storm preparation (crew and equipment pre-positioning)
 - b. Outage prevention (tree trimming, addition of reclosers and sectionalizers, hardening (underground cabling), equipment (transformer) replacement, load analysis (positive or negative flow))
 - c. Service restoration (crew dispatch, switching)
 - d. Increased EV load and/or PV generation accommodation
 - e. New commercial EV Supply Equipment (charging stations) location and sizing
- 4. AI-based power flow with a limited network model



Thank You! Questions?



John Dirkman, P.E. VP, Product Management

John Dirkman P.E., Vice President Product Management for Resource Innovations, has over 30 years of experience as a Product and Program Manager, developing and implementing advanced integrated Smart Grid systems from concept through marketing, business development, design, coding, testing, implementation, and maintenance. His experience includes development of ADMS and DERMS solutions that include a transactive market platform to enroll and contract for services to leverage and accelerate adoption of distributed energy resources. He has experience integrating systems including ADMS, OMS, EMS, SCADA, AMI/MDM, IoT, GIS, CIS, and cybersecurity. He is responsible for driving Resource Innovations' Smart Grid vision and strategy and ensuring product success in the marketplace. Mr. Dirkman has been with Resource Innovations/Nexant since 2015 and was previously with Schneider Electric for 13 years, James W. Sewall Company for 3 years, and the US Army Corps of Engineers for 8 years. He is a registered Professional Engineer, a Senior Member of the IEEE Power & Energy Society, an inventor and entrepreneur, has served as an Adjunct Professor at Northwestern University, and has given over 75 webinars and presentations at utility conferences. More information can be found on his LinkedIn profile: www.linkedin.com/in/dirkman





Can Al get us to net zero?

Nora Esram, Ph.D.

November 21, 2024





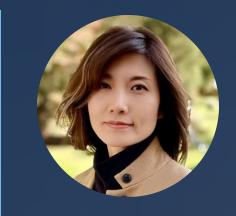
About ACEEE:

The American Council for an Energy-Efficient Economy (ACEEE), is a nonprofit research organization that develops policies to reduce energy waste and combat climate change. Its independent analysis advances investments, programs, and behaviors that use energy more effectively and help build an equitable clean energy future.

Learn more at aceee.org



Presenter



Nora Esram, Senior Director of Research, ACEEE

Dr. Esram currently serves as the Senior Director of Research and is a key member of the executive team at the American Council for an Energy-Efficient Economy (ACEEE), where she oversees the organization's research programs, including Buildings, Industry, Transportation, and Behavior and Health. In her previous role as Chief Engineer at the Pacific Northwest National Laboratory, she led large, multi-disciplinary projects dedicated to advancing energy efficiency, sustainability, and decarbonization. Her current research areas include embodied carbon, electricity demand growth, and the role of Al in enhancing efficiency.



A Dual Challenge: Al and Load Growth

Projection: Electricity demand is expected to rise rapidly, driven by AI data centers, electrification, and new manufacturing facilities, putting increased pressure on the electric grid. The grid will need to expand by 33% to 67% in a decade, with a growth rate ranging from 2.6% to 4.7% 6 TWh 5 TWh 4 TWh

2010-2023: Electricity demand remained nearly flat over the past decade, partly due to the economic downturn until the end of the pandemic

3 TWh

2 TWh

1990-2000: Electricity demand grew steadily at an average rate of 2% per year, driven by the rise of digitalization

energy efficiency

2000-2010: Electricity demand

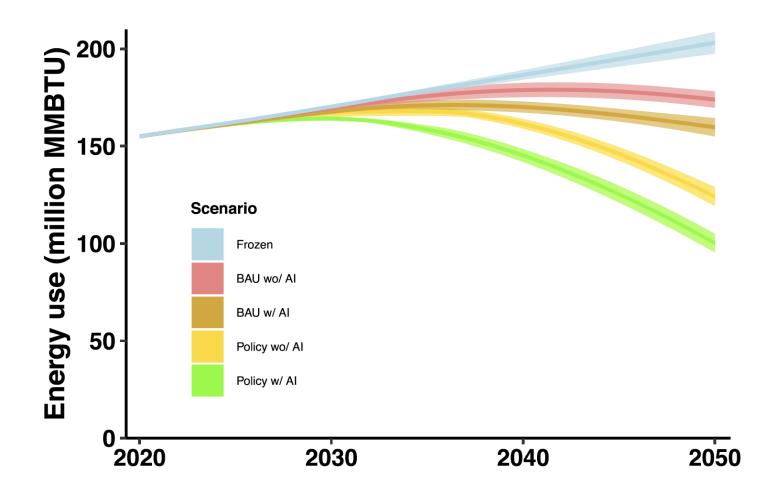
growth slowed to 1%, even as cloud services quickly expand, with some of the demand growth being offset by improvements in

2030

Promising Solutions

- Flexible demand powered with carbon-free electricity:
 - reduce energy consumption during grid strain
 - ramp up usage during renewable energy surpluses
 - store excess electricity to feed back into the grid
- Al can potentially help solve complex grid optimization problems, dynamically balancing supply and demand and harnessing the full power of renewable energy, **but only if we train it to.**

Potential of AI in Reducing Energy and Carbon Emissions of Commercial Buildings



Adopting AI could reduce energy consumption and carbon emissions by approximately 8% to 19% in 2050.

Combining with energy policy and low-carbon power generation could approximately reduce energy consumption by 40% and carbon emissions by 90% compared to business-as-usual scenarios in 2050.

Source: Ding, C., Ke, J., Levine, M. et al. (2024)

Examples of AI Applications in Buildings

- **Equipment:** failure detection, predictive maintenance
- **Design:** BIM model checking, architectural design optimization
- **Construction:** Project schedule optimization, drone/robotic construction, 3D concrete printing/digital construction
- **Operation:** Fault detection diagnostics (FDD), model predictive control (deep learning, reinforcement learning)
- Occupant behavior: smart occupancy sensor, behavior prediction



Potential Applications of New Al Capabilities

- Chatbots could help individual homeowners make informed electrification choices based on their home energy systems, needs, and conditions. Similarly, they could educate commercial building owners and managers about their building energy systems, helping them decide which technologies to install and when to use them.
- ML could help with data processing, giving building operators and service providers a better understanding of interactive variables in a building. ML could run multi-dimensional models to support energy management and control strategies.
- Al could use images to help **energy modelers and utilities** better understand building characteristics and surroundings, validate measured or modeled data, and make more informed design or program decisions.
- Grid managers could use AI to balance demand and supply by more quickly finding available demand-side resources and optimal solutions based on grid capacity.



Challenges and Limitations

- Some operations are more constrained by financial considerations than by advanced technologies. Savings can be achieved without necessarily investing in expensive new technologies like AI.
- The data used to train AI might be biased in some ways and not truly representative of building conditions and occupant needs.
- Al could help sequence operations for demand response, but connectivity through proprietary API can complicate these efforts.



Collaboration Opportunities

- Illustrate the costs and value propositions of AI applications.
- Develop frameworks to guide decision-making in AI adoption.
- Engage venture capitalists and connect AI developers and energy professionals.
- Incentivize the installation of AI-ready hardware to facilitate the adoption of more advanced smart building solutions as the technology matures.
- Develop policies to use demand-side strategies in coordination with energy generation and transmission.



Contact

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References

- Ding, C., Ke, J., Levine, M. et al. Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. Nat Commun 15, 5916 (2024). <u>https://doi.org/10.1038/s41467-024-50088-4</u>
- Esram, N & Elliot, N. Turning Data Centers into Grid and Regional Assets: Considerations and Recommendations for the Federal Government, State Policymakers, and Utility Regulators. ACEEE. (2024). <u>https://www.aceee.org/policy-brief/2024/10/turning-data-centers-grid-and-regional-assets-considerations</u>



Additional slide: Data centers are driving massive growth in electricity demand—just as U.S. manufacturing is surging

- Electrical load growth puts achieving carbon goals at risk.
- The increase in demand is not uniform.
- Data centers can increase household energy bills and affect environmental quality.
- Data centers generate limited long-term local jobs, although they bring tax revenue.
- Conventional efficiency measures and operational optimization are inadequate to manage GenAl data centers.

Dominion Electric took 115 years to reach its current power delivery capacity. However, with the rapid growth of data centers in Virginia, Dominion is on track to double its system load within the next 15 years.

When data center water consumption is concentrated in a small region, it can account for a quarter of a town's annual water consumption.

Traditional data centers consume around 7.5kW per rack of servers. Al data centers operate above 30 kW/rack, and emerging designs will require 100 kW/rack.



Upcoming conferences

Energy Efficiency Policy Forum	December 3, 2024	Washington, DC
Hot Water & Hot Air Forums	March 4–6, 2025	Portland, OR
Summer Study on Energy Efficiency in Industry	July 16–18, 2025	Charlotte, NC
Energy Efficiency as a Resource	October 7–9, 2025	Denver, CO
2026 Summer Study on Energy Efficiency in Buildings	August 2–7, 2026	Pacific Grove, CA

