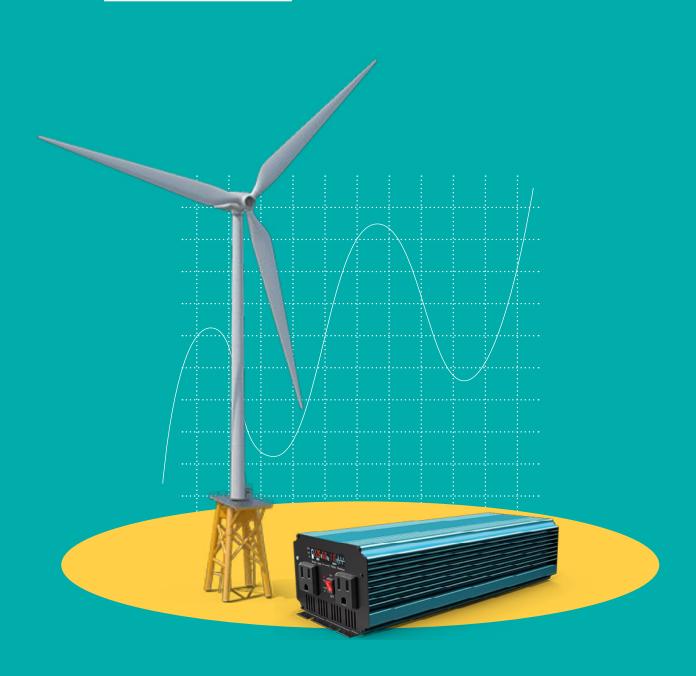




Powering the Future: Use Cases for AI in Utilities & Energy



INTRODUCTION

In the coming years, the world will watch as AI, machine learning, and data science transform the economy and our day-to-day lives. Perhaps no AI-enabled change has greater implications for mankind, however, than the reshaping of the energy sector.

The energy sector is generally regarded as conservative in mindset and therefore slow to adopt digital technology. After all, much of the technology that powers modern life — coal, oil, the electrical grid — has remained largely unchanged since the late 19th century. Yet a 2017 McKinsey report classified resources and utilities as in the middle of the pack in terms of digitization, above retail, education and health care but behind financial services, automotive and manufacturing and, of course, the technology sector.

However, the last few years have seen significant technological changes in the energy economy:

- Oil and natural gas prices are low because of pioneering technology that allows companies to affordably access resources that were previously considered uneconomical.
- Electric utilities are using machine learning to better understand their customers and deploy their resources more efficiently, cutting costs for the utility and consumers alike.
- Meanwhile, the prospect of a renewable revolution becomes more realistic by the day largely because of major advances in AI that help generators maximize the impact of the sunshine and wind they are harnessing.

The drive to make utilities more efficient through AI, machine learning, and data science has resulted in major benefits for every actor in the energy sector, including generators, distributors, the environment, taxpayers, and consumers. There is still much to do, however, and resource and utility companies that hope to remain competitive in the coming years should be aggressively pursuing the next technological frontier.

This white paper will cover some of the highest-value use cases in the utilities and energy industries as well as suggested paths to scale up AI competencies within these organizations.



HIGH-VALUE USE CASES

Overall, use cases for data science, machine learning, and AI for utilities fall into one of five categories:











SPEED-TO-VALUE & TEAM EFFICIENCY (ORGANIZATION)

FORECASTING: PREDICTING ENERGY SUPPLY & DEMAND

The last few years have seen an explosion in the number of connected devices, notably residential smart meters. In 2007, there were fewer than 5 million U.S. <u>customers with smart meters</u>. A decade later, the U.S. Department of Energy reported there were already roughly 79 million advanced smart metering installations in the United States., accounting for roughly half of all electricity customers. The great majority (70 million) were residential, followed by commercial (9 million), industrial (365,000), and transportation (1,389).

There remains significant room for continued smart meter adoption in the United States and other industrialized countries. In the developing world, the potential is even greater.

Research and Markets projects the number of smart meters in the U.S. and Canada will rise from 100 million in 2018 to 143 million by 2024. China has embraced smart meters with even greater enthusiasm: it had just under 500 million meters installed in early 2018, and in recent years, it has accounted for the majority of worldwide installations.

Smart meters are helping consumers better calibrate their energy use, but more importantly, they are helping utilities to better understand and manage their load. Some utilities in the United States have put in place load management programs that customers with smart meters can opt into. These allow the utility to remotely reduce a customer's energy consumption in order to reduce peak load. This reduces overall energy consumption, increases affordability for customers, and allows the utility to forgo major infrastructure investments necessary to bolster peak load capacity.

Of course, there are inherent organizational and technological challenges to overcome when it comes to actually leveraging sensor data effectively. While many companies have long managed very large data sets, sensor data from connected devices and smart



meters is many orders of magnitude beyond what companies have traditionally managed. In addition, the types of information sensors collect is highly diverse and expanding daily. It also tends to be unstructured, which means that it either does not have a predefined data model or is not organized in a pre-defined manner.

Therefore, proficiency in collecting, processing, storing, managing, and analyzing extreme data sets is a must-have for data teams in the energy domain. It's a daunting task that depends on many competencies unlikely to be found in a single person, and it's a challenge that goes beyond just people. Transforming extreme data sets into actionable insights and business innovation requires the right people, processes, and tools.

GO FURTHER

Data science, machine learning, and AI platforms are tools that can help organize processes and people around data projects and pipelines to get value from raw data, faster. Read more about the benefits and what to look for.



One of the challenges this use case poses is that a more connected grid has major implications for grid reliability. Notably, it counters the challenges to reliability brought on by the rise of renewable power and the threat of attacks on the power grid from terrorist groups.

The rise in renewables has led to a greater number of generation sources and consequently, a more complex grid. In that context, ensuring reliability becomes more complicated, not only due to the greater number of energy sources but the fact that many of the renewable generators only provide intermittent energy linked to whether the wind is blowing or the sun is shining.

Another concern: acts of sabotage that could produce devastating grid disruptions. Many critical assets are located in sparsely populated areas with little to no protection from determined vandals, let alone a coordinated attack by a terrorist organization. A successful attack on just nine substations — many of which are only minimally protected — could take down the entire <u>U.S. power grid.</u>

Fortunately, the increased prospect of disruptions has been accompanied by the adoption of digital monitoring systems that can more accurately forecast the power needed to ensure a reliable and resilient grid. Just as important, Al capabilities are helping utilities to more quickly detect disruptions, from a downed power line to the shutdown of a major plant.



Al-enabled systems can offer effective, affordable security to protect valuable assets from attacks and reduce the need for on-site security staff. Power Magazine describes the potential of tower-mounted robots that monitor the surroundings and can automatically detect human intruders:

Such technology connected to a high-speed network could transform a power grid's passive security system into an active defense-and-denial physical protection system. Using non-lethal actuators, such as cameras and sensors, the system detects, delays, and safely thwarts a potential attacker by overwhelming them with directed, high-intensity sound, lights, and strobes.

The increased complexity of the grid has prompted operators to adopt more sophisticated digital tools to monitor conditions. Even better, with machine-learning capabilities, the systems, some of which can "measure the amplitude and phase of current and voltage up to 50 times a second," store and analyze years worth of data that allow them to anticipate future disruptions.

Recently, researchers in Germany have pioneered an Al-enabled technology that can automatically "log, compress and process up to 4.3 million data sets per day," according to Peter Bretschneider, chair of the Energy Department at the Fraunhofer Institute of Optronics, System Technologies and Image Exploitation. The Fraunhofer team fed neural networks with examples of system outages to teach the system how to properly identify and predict future threats to grid reliability.

The ability of AI to more precisely forecast load will play a major role in reducing overall energy consumption. Systems that are able to forecast peak load will allow utilities to even better align their resources with demand and minimize waste.

For at least two years, Google's DeepMind and National Grid, which runs the United Kingdom's electric grid, discussed partnering in an effort to reduce energy consumption by 10 percent. While the collaboration never came to full fruition, there is little doubt that the world has not seen the last of large-scale AI-powered efforts to reduce energy consumption.

GO FURTHER

Because of its wide array of applications, mastering anomaly detection in the age of AI is incredibly valuable, especially for the utilities industry for use in forecasting and demand prediction.

This quidebook features:

- A breakdown of the types of anomalies and anomaly detection use cases.
- A step-by-step guide to running a machine learning-based anomaly detection project, both from a business and a technical perspective.
- A walkthrough of an example use case, including code samples.



PREDICTIVE MAINTENANCE

As is the case with virtually every industry, utilities stand to gain a lot from using AI for predictive maintenance. For utilities, the reliance on extraordinarily expensive equipment and infrastructure makes the potential for cost-savings, operational improvements, and liability reductions even greater. A Deloitte white paper put the challenge in context:

The possibility of an aging stretch of buried pipeline becoming unstable one day, perhaps after new above-ground construction moves ever closer, presents a level of risk few other industries face.

As the Deloitte analysis explains, utility assets face a myriad of potential risks that aren't present in a more controlled industrial environment, such as a factory or warehouse. There is always the potential of weather events or encroaching construction disrupting or damaging vital assets, requiring close coordination between utilities and other entities, including local governments and private property owners.

How can a utility foresee potential issues and prioritize assets for repairs or maintenance? Traditionally, that work is done by a team of highly skilled engineers, who make educated guesses about which assets are most likely to falter in the near future based on age, surrounding conditions and other key data.

Increasingly, utilities are using data science to deploy predictive algorithms that can:

- Incorporate far more variables into the prioritization process.
- Identify factors that engineers otherwise would not have considered.

For instance, they may recognize a correlation between asset performance and geography that may have eluded human detection. Out of this complex analysis comes a risk modeling that will triage maintenance tasks based on the significance of the project and time-sensitivity. That means that increasingly, utilities will be able to move forward with maintenance confident that they are deploying resources to the most important, time-sensitive projects.



It's not just the utilities themselves who are achieving cost-savings and operational enhancements through sophisticated Al-enabled predictive maintenance solutions, but the entire energy sector that utilities depend on, notably in the extraction and transportation of resources.

Oil and gas extraction companies are deploying machine learning applications that monitor the wear and tear on pumps to predict and prevent failures that could result in major slowdowns and expensive repairs or replacements.

Another major maintenance challenge for energy companies relates to the storage and transportation of crude and refined oil. The corrosion of storage tanks and pipes is a constant risk, and it's exceedingly difficult to forecast the impact of corrosion due to the wide variation in chemical composition of crude oil. The environment the crude is stored in also raises or reduces the potential for damaging corrosion.

Most energy companies are already using continuous monitoring technologies - like Internet of Things (IoT) connected devices - which is a good start; but the key lies in not just simply monitoring the output of various data (which is how many companies use it today), but by taking the next step and employing advanced algorithms and machine learning to take action from real-time insights.

Going one step further, the biggest area of opportunity in predictive maintenance for the utility and energy sector lies in rethinking and optimizing the entire maintenance strategy as a whole from top to bottom, creating larger, Al-driven systems that take the best series of actions based on the risks at hand. This means:

- Considering a combination of maintenance strategies to determine the optimal cost-saving combination of predictive and traditional maintenance, perhaps even on an asset-by-asset basis.
- Creating Al systems that optimize for (and automate) the immediate next steps once predictive systems point to imminent
 failure, whether this automatically triggers a work order, notifies a technician or certain team, places an order for a
 replacement part, etc.
- Identifying how to best execute necessary repairs through second-order or secondary analytics, meaning having a process in place for an entire deeper layer of analysis to determine the best time to actually remove the asset from service and which additional repairs if any should be conducted simultaneously to minimize the cost of having to remove the asset again for a different failure within a short window.
- Determining if, through predictive maintenance, assets now have extra capacity due to decreased overall downtime and whether that time can be sold to other (generally smaller) businesses.

GO FURTHER

Predictive maintenance is an obvious first step into data science for any business with high-capital assets. By harnessing machine learning to control rising equipment maintenance costs, utilities can pave the way for self maintenance through AI.

This step-by-step guidebook breaks down:

- The differences between traditional and predictive maintenance.
- Use cases & potential data sources.
- Specific challenges to exploring, cleaning, and modeling data for predictive maintenance.



PREVENTING ENERGY THEFT

In many parts of the world, energy theft is a major challenge for utilities, governments, law enforcement, and society as a whole. Worldwide, it was estimated that 8.3 percent of energy consumed in 2016 was stolen.

A notable victory for Al over theft came in Brazil, the world's tenth-largest energy consumer. Until recently, it was estimated that 8 percent of Brazil's energy was being stolen from the grid. In some areas, the portion of stolen power was as high as 40 percent. Beyond the issue of power being produced that isn't being paid for, the widespread theft made it difficult for utilities to accurately assess the true demand in the system and build infrastructure to accommodate it. The lack of information resulted in an unreliable electric system that was prone to blackouts. It also imposed a significant cost burden on other residents and businesses that were forced to pay for the stolen electricity.

Fortunately, in 2011, a Brazilian startup, Senergy, collaborated with Siemens engineer Sergio Jacobsen to analyze data from the 122,000 smart meters throughout the country. It took nearly a year of receiving and interpreting data from smart meters, but eventually the team was able to zero in on the source of the issue: small- to medium-sized businesses that were <u>illegally connecting</u> to the grid. ⁹

Siemans' findings prompted a \$700 million collaboration with Eletrobras, Brazil's largest utility, and the World Bank, to crack down on energy theft. Long-term, Senergy is using algorithms to create complex user profiles that compare energy consumption to the amount of energy that is actually coming off the grid. Utilities can use that information to identify and investigate theft.

Again, one of the keys to execution in detecting energy theft is being able to combine data from many varied sources to see patterns and insights that would be undetectable with manual or human analysis.

As with many of the use cases discussed in this white paper, that doesn't necessarily mean hiring a slew of data scientists. Rather, today's top companies are able to find success in arming business experts (who are already familiar with the industry, the specific company, and its particular challenges) with tools that allow them to work with data at scale and code-free - including incorporating machine learning with AutoML features.

GO FURTHER

Learn more about AutoML why it's a big part of the future of AI in the enterprise (including for utility and energy companies), and how it can help turn existing employees into citizen data scientists to get started with AI initiatives now.







OIL & GAS EXPLORATION

Even as fracking has transformed the oil and gas industry, opening up resources that were previously viewed as too expensive to access, the industry constantly faces challenges over the cost of exploration and extraction. When oil prices are low, as they have been in recent years, upstream companies face tough decisions about where to invest limited resources. They need to be extremely wary of avoiding uneconomical wells where the high cost of extraction makes it impossible to turn a profit.

For starters, new programs are able to help companies more quickly identify and acquire property. Al-powered applications are able to continuously analyze public databases of tax records, property deeds, and even death certificates and alert management to properties that might be eligible for acquisition and exploration.

Similarly, exploration and production companies are turning to "case-based reasoning," a type of AI that searches through databases of other projects to identify those with similar conditions, the reported problems they encountered and how they were resolved. As is the case with so many AI applications, the goal of CBR is not to supplant human knowledge but to more fully harness it and maximize its impact.

Companies are leveraging AI to enhance operational planning, with an eye toward reducing risk when digging wells. AI programs can quickly process data that planners might be either interpreting in a simplified format or not considering at all, simply due to the sheer volume of data. For instance: pump speeds, valve positions, flow rates, temperatures and pressure differentials, thermal gradients, strata permeability, seismic vibrations, and weather.

Al continues to play an important role during the drilling process, as Al-enabled programs monitor the performance of the equipment (see the previous section on predictive maintenance), automatically making adjustments to maximize efficiency and safety.

Automated programs that are able to alter speed, direction, pump strokes, penetration rate and chemical injection rate based on conditions are able to operate with far greater precision than individual employees and are far less prone to error, lapses in attention, fatigue or the myriad other human-specific challenges that can lead to accidents or inefficiencies.

RENEWABLE POWER



Al is most certainly going to play a major role in boosting renewable energy. While renewable sources, notably solar and wind power, are on the rise, they are still not capable of being the dominant energy sources due to their intermittent nature.

While there have been promising advances in battery storage technology that allows utilities to store power generated from intermittent sources and dispatch it when needed, the devices remain too expensive for widespread adoption. That explains why, despite investing heavily in renewable projects, China also continues to build new coal plants at breakneck speed. And while renewables have surpassed coal in the United States, they still lag far behind natural gas, which is both cheap and dispatchable.

Data is the key to helping utilities make the most of available renewable sources. For example, Al-powered predictive analytics based on historical data help utilities forecast the weather with a precision that would have been unfathomable until recently.

Being able to predict how much sun or wind will be available two hours from now allows utilities to determine how much generated energy they should store.

Predictive analytics will also help utilities optimize the search for wind or solar-generating properties, so that they can know exactly how much power a given parcel of land is expected to produce.

Money is pouring into ventures aimed at making renewable power more cost-effective through digital technology and Al. In fact, conventional energy giants, such as ExxonMobil, Southern Company and Tokyo Gas are investing in renewables in anticipation of a greener energy economy in the coming decades. In Texas, the longtime heart of America's oil and gas economy, is also the source of much of the country's emerging wind sector; ExxonMobil is powering its oil operations in the Permian Basin with wind energy.



CONCLUSION

NEXT STEPS FOR UTILITIES IN THE RACE TO AI

There's no doubt that today, utility and energy companies are handling increasingly more (and increasingly more complex - think videos, images, sound, etc.) data, which will inevitably require more complex algorithms. More complex algorithms are able to learn hidden patterns from the data by itself, which is why they are useful - they can deal with problems that a human brain could not understand. And that's why utilities and energy companies that are able to incorporate AI into their overall business strategy first will get ahead.

But execution is easier said than done, and it requires orchestrated coordination of not only technology, but perhaps more importantly, people and processes as well. Indeed, businesses that have seen the most success in using data to drive profit are those willing to put data in the hands of the many and not just the elite few (like data scientists or even analysts).

That means immediate next steps for companies looking to advance in the race to AI include:

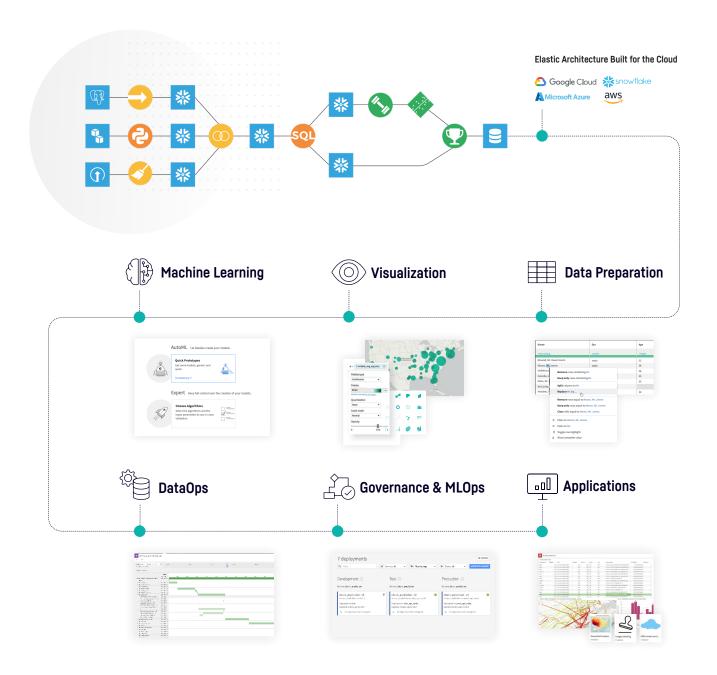
- 1. Working toward **data democratization**, meaning alignment of processes around access to data at all levels of the organization. This may mean investing in tools that provide easy (yet controlled) access to data, collaboration, documentation, and AutoML features.
- **2. Education** of all people at the organization surrounding the importance of data-driven decisions as well as possibly the **basics on machine learning**, **deep learning**, and **data architecture**.
- 3. An investment in **tools that enable** both data democratization and education, but that are also cutting-edge (think leveraging open source) and elastic, flexible to the needs of both today's and tomorrow's organization.





Everyday AI,

Extraordinary People



45,000+ 450+ customers

Dataiku is the platform for Everyday AI, systemizing the use of data for exceptional business results. Organizations that use Dataiku elevate their people (whether technical and working in code or on the business side and low- or no-code) to extraordinary, arming them with the ability to make better day-to-day decisions with data.

