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AN INTRODUCTION TO AI, ITS USE CASES, AND REQUIREMENTS FOR THE ELECTRIC POWER INDUSTRY

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Executive Summary

The trends of decarbonization, decentralization, and digitalization are driving a massive shift in the power industry. Electric utility customers now expect a higher level of service not only in terms of value, speed and reliability but also in sharing information from customer to utility and vice-versa. These trends necessitate deployment of analytical tools that can take data streams from different components of the grid and provide actionable intelligence to all stakeholders.

Artificial Intelligence (AI) is one such powerful tool that has tremendous application potential in the electric power industry. Commoditized computation power, better and efficient algorithms and, massive data generated within the industry are all necessary for successful application of AI in the industry. Numerous use-cases are being explored in the industry ranging from energy production from wind farms to automating asset inspection programs.

This white paper provides an overview of AI and its common methods. Moreover, it describes current use cases and challenges in applying AI in the power industry. At the center of these challenges is a lack of data and a lack of understanding of how AI technologies can be tailored and used in the power industry.

The Electric Power Research Institute's (EPRI) AI initiative is focusing on accelerating the adoption and application of AI.

Introduction

Utilities continue their rapid transformation enabled by decarbonization, decentralization, and digitization; moving from centralized generation and interconnected transmission and distribution networks to renewable generation, flexible gas-fired generators, and distributed energy resources like photovoltaics and energy storage systems.

Meanwhile, utility customers are also becoming more sophisticated, with increasing expectations for value, speed, and reliability. Whereas the utility grid once terminated at the customer's meter, today that customer is an active participant in the integrated grid thanks to the proliferation of connected devices enabled by the Internet of Things (IoT).

Shift in the Power Industry

The shift in the power industry is caused by decentralization, decarbonization and digitalization. This shift requires new tools and technologies to address the challenges caused by the shift.

Artificial Intelligence

AI is defined as the science and engineering of making intelligent machines, especially intelligent computer programs.

Challenges of Applying AI

A feasible AI solution requires big data, suitable platform and computer science experts and the power industry has to refocus its business to address these.

And we are just getting started. Electrification—the application of energy-efficient electric technologies as alternatives to fossil-fueled or non-energized processes—is set to disrupt the transportation industry. Electric vehicles create a new class of mobile load that the industry is learning to manage.

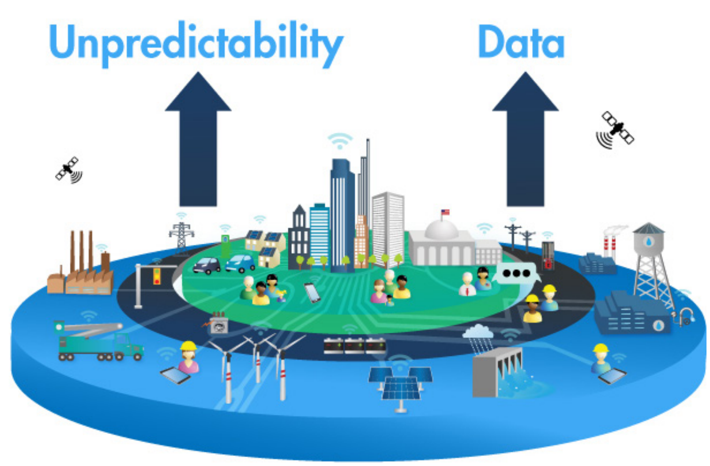


Figure 1. Data has multiplied as unpredictability has risen

While the electric power industry is looking for new tools to address these challenges, the industry has been modernizing itself for decades in an effort to provide safe, reliable, affordable, and environmentally responsible power. Examples of these modernization efforts include digitization in generating stations, sophisticated control systems managing the grid, and installation of advanced metering infrastructure.

These modernization efforts help reduce operations and maintenance costs as well as provide tools to better manage and optimize the highly unpredictable grid. But there is another key benefit—data (see Figure 1). The large volumes of data now available on asset health, condition, and utilization can help utilities make better decisions. Several electric utilities have established analytics teams that are collecting, managing, and analyzing this data. The commonly used techniques and methods for doing this still require human supervision. The industry is looking for faster and less expensive tools that provide better insight using data.

Given its tremendous capabilities and potential, Artificial Intelligence (AI) can become an integral part of this toolbox. The latest surge in AI is enabled mainly by the convergence of commoditized computation power, new algorithms (such as deep learning), and big data. These three pillars are the basis of a sustainable AI solution.

AI has potential applications in many areas of the power industry, including generation optimization, asset management, and load shaping. For example, renewable generation can take advantage of AI's capabilities to better predict energy production. AI can also be used to increase production by, for instance, adjusting positions of the solar arrays based on sun and cloud positions. Asset inspection decision-making processes can be automated using numerous AI techniques, eliminating or reducing need for repetitive and labor-intensive tasks like analyzing thousands of images. For behind-the-meter technologies like air conditioning and charging electric vehicles, AI can be used for targeted energy efficiency measures or demand response.

As a primer of a technology not yet well studied in the electric utility industry, this paper defines commonly used terms, investigates the requirements of applying AI, and presents use cases.

This paper is the first in a series. Subsequent papers will detail AI methods and their potential applications in the electric power industry.

Terminology

Artificial Intelligence

There is no single and precise definition of artificial intelligence. John McCarthy, considered a founding father of AI, defines it as "the science and engineering of making intelligent machines, especially intelligent computer programs." Loosely speaking, AI is defined as how machines can imitate human intelligence (being human-like rather than becoming human), such as learning from experience. AI is based on a variety of sciences, including mathematics, statistics, cognitive science, philosophy, and linguistics.

An example of AI is the voice assistants commonly available on phones and now on various smart home devices. These devices learn to recognize a voice and, over time, get better at executing commands or transcribing text. Just like humans, these devices can account for changes in input voice (maybe a different accent) and still do a decent job. As more data (voice samples) are captured, the accuracy of the device improves.

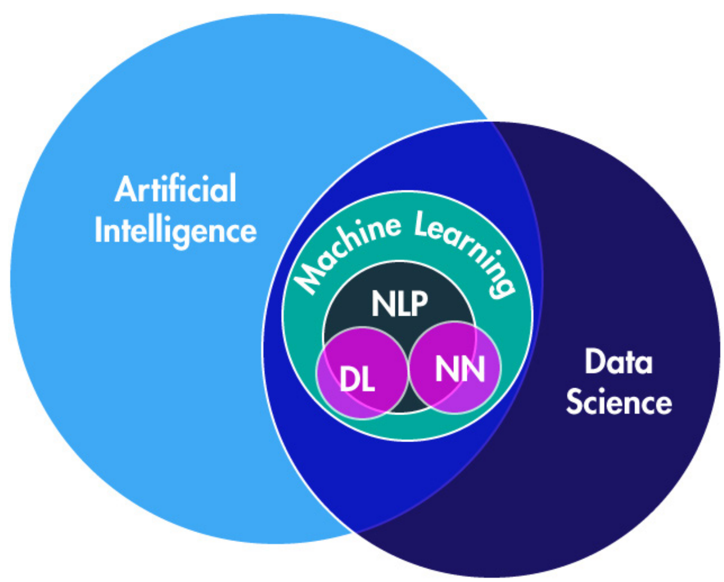


Figure 2. Relationship between AI concepts. DL stands for deep learning and NN stands for neural networks.

Machine Learning

Sometimes used interchangeably with AI, machine learning (ML) is the study of data-driven computer algorithms that improve automatically through experience. Machine learning is one of the ways that AI is expected to be achieved. Deep learning, natural language processing, and neural networks are among the many approaches to machine learning. Figure 2 shows the overlap in and relationship between AI, ML, and the other approaches.

Supervised Versus Unsupervised Learning

Two types of machine learning tasks are supervised and unsupervised learning. Supervised learning is the more commonly used type. In supervised learning, the learning is done using a ground truth, where there is prior knowledge of what the output values for a sample data set should be. Therefore, the goal of supervised learning is to learn a function that best approximates the relationship between a data sample and the desired outputs (see Figure 3). This function then can be used to predict the output for a given input data set. Supervised learning is mainly used for classification problems; common algorithms include regression, support vector machines, artificial neural networks (ANNs), and random forests. An example of supervised learning in the power industry is asset management, such as when images taken by drones are analyzed to recognize damaged transmission and distribution equipment. This application requires the images to be labeled, for instance, as an image representing a healthy asset or an unhealthy asset.

Unsupervised learning, on the other hand, does not require labeled data. In this type of learning, the goal is to learn an inherent structure within a set of data points. Unsupervised learning is a more complex problem compared to supervised learning and can be used for many problems that humans cannot tackle easily. Unsupervised learning is mainly used for clustering problems (see Figure 3). K-means clustering, and principal component analysis are among the algorithms used for unsupervised learning. In the previous example of supervised learning using images of damaged assets, unsupervised learning could accelerate the process by clustering similar images, allowing a human to label just one image per category.

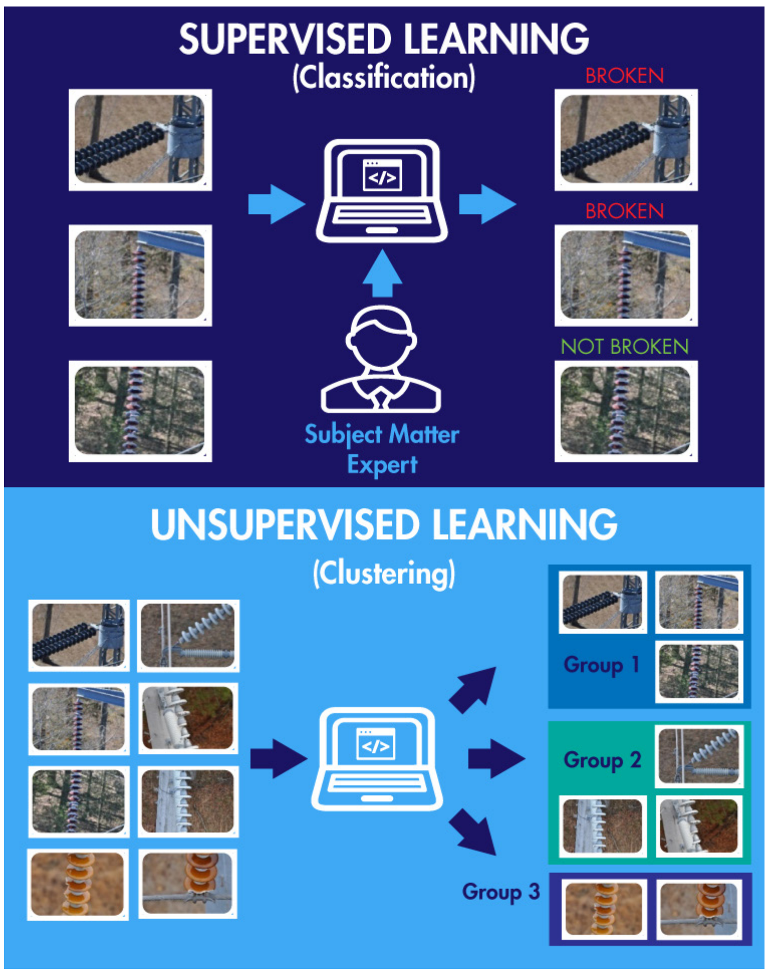


Figure 3. Classification vs. clustering

Natural Language Processing

Natural language processing (NLP) helps computers capture, interpret, and make sense of human languages. NLP is drawn from many fields, including computer science and linguistics, and it is widely used for tasks such as text analysis and creating chatbots. Depending on the problem, both supervised and unsupervised learning methods are used for NLP.

One industry-specific application of NLP is the processing of documents such as injury reports to analyze and make recommendations for safe operations. Another example is chatbots, which some utilities use to assist customers.

Artificial Neural Networks

Artificial Neural Network (ANN), a main tool in machine learning, is inspired by the function of the human brain. Neural networks consist of input and output layers as well as a hidden layer that transforms the input so that it is usable by the output layer. These networks have been around since the 1940s, but the rise in their application in the last couple of decades is due to the backpropagation technique that enables the hidden layer to adjust its parameters if the output of the neural networks is not the desired output. These networks are often called shallow because they have one hidden layer, whereas an ANN with multiple hidden layers is a deep neural network. This distinction is illustrated in Figure 4.

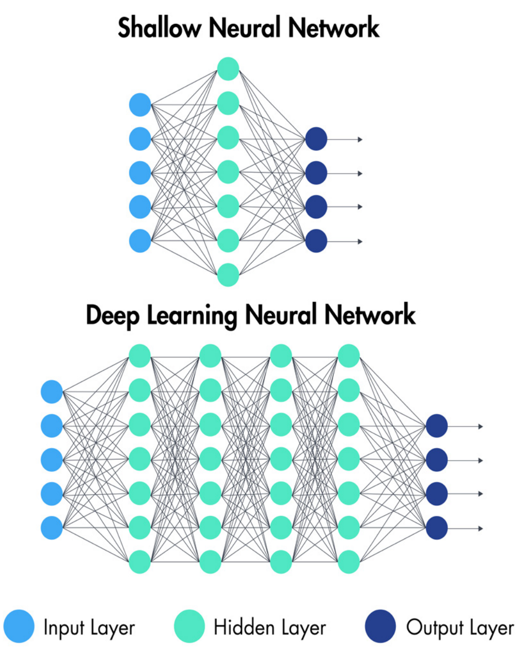


Figure 4. Comparison of a simple and deep neural network

Deep Neural Networks

Deep neural networks are basically neural networks that learn from a large amount of data. In a deep neural network, the algorithm performs a task repeatedly, each time adjusting it to improve the outcomes. Deep refers to the neural networks having various layers. In other words, a deep learning algorithm can improve its performance by accessing more data—which, for a machine, is the human equivalent of having more experience. A deep learning algorithm eliminates the need for manual feature extraction and uses its learning process to discover the patterns in data. Therefore, training neural networks becomes much faster and yields better results. Multilayer perceptrons, convolutional neural nets (CNNs), and long short-term memory are three common algorithms of deep learning.

Image recognition for identifying damaged assets and predictive maintenance applications for assets are examples of ANN's and deep learning algorithms applied in the power industry.

AutoML

AutoML is the end-to-end process of automated application of machine learning to real-world problems, such as data preparation, feature engineering, and model selection. It is gaining attention due to the lack of expertise in applying machine learning techniques.

Structured Versus Unstructured Data

The term structured data refers to data that have a defined model, format, or structure and reside in a database. Analysis of this type of data is well studied. Examples of structured data are workflow, process, Web data, or data collected from IoT devices. On the other hand, unstructured data do not have any inherent structure and are usually stored as types of files, such as PDFs, images, video, and texts. Unstructured data appear in the power industry as asset images, manuals, asset drawings, and so on. Figure 5 illustrates different types of unstructured and structured data.

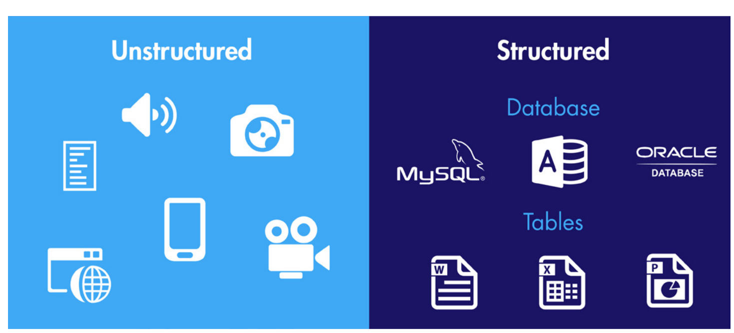


Figure 5. Examples of unstructured and structured data

Use Cases of AI in the Power Industry

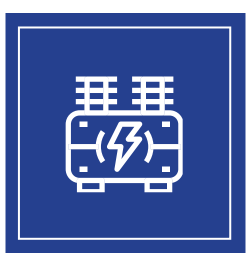
Even though AI is not being applied in the power industry extensively, the following use cases demonstrate how the capabilities of AI are being exploited.

Wind Energy Forecasting

Despite the recent surge in renewable energy generation, the intermittency of these resources poses many challenges to utilities. Utilities must be able to predict wind speeds and direction with high accuracy in order to rely on this renewable resource.

Xcel Energy partnered with the National Center for Atmospheric Research (NCAR) to develop a wind power forecasting system. This system relies on AI technologies to create a high-resolution wind forecasting hybrid model based on Xcel's data on wind and power output from sensors on its wind turbines combined with NCAR's data collected from local weather stations, satellites, and so on. Their hybrid model includes different prediction modules, and machine learning adjusts the dependency of the final predictions on each module. This model has reduced the wind forecast margin error by 40% [1, 2].

Transformer Heath Management



With the current shift in the power grid— specifically, the increasing integration of renewable energy resources—transformers are under more stress. This poses a new challenge for the power grid because many transformers lack effective real-time monitoring and diagnostics.

In the wake of two transformer failures, New York Power Authority partnered with mPrest and EPRI to develop a monitoring and diagnostics system for the transformers at its power plants. This system uses real-time and historical data collected from sensors on transformers. Then, a combination of a machine learning algorithm and rule engine uses these data plus external lab report data to detect anomalies in the transformer's health data. This system could have prevented an actual transformer failure because it detected anomalies in the data well before the collapse occurred [3, 4].

Intelligent Energy Storage Management

In a decentralized grid, virtual power plants (VPPs) are critical elements. VPPs should be well integrated into the broader grid, which poses some challenges for the utilities in terms of demand prediction and generation-demand balance.

Hawaiian Electric, in partnership with Stem Inc., has completed a one-megawatt intelligent storage system to accommodate renewable energy resources in its territory. This system has an analytics model that uses the weather forecast as well as historical and real-time usage data to predict the peak load periods in a site. The system then draws on stored power to reduce the customer's cost. Moreover, by combining these data with predictions for Hawaiian renewable generation, the utility can use the stored electricity in conjunction with solar generation to increase grid stability [5].

Challenges

Even as AI technologies gradually make their way into the power industry, there are numerous challenges throughout the workflow to be addressed. A typical workflow of an ML project involves defining the problem, data processing and segregation, model training and evaluation, deploying the model, and performance monitoring.

Data Availability

Many AI technologies require a vast amount of data for training. Data streams generated from different sources in a single utility are usually not enough to result in acceptable performance from a model, especially when using deep learning algorithms. For instance, training a good image recognition model using CNN requires thousands of images that include failed and healthy assets —a logistical hurdle for the utility that wants to train a model to classify its assets using only its own data.

Data Processing

Preprocessing of data, which mainly includes labeling, is time-consuming and expensive. Two methods can be considered for labeling data: manual labeling and manual labeling in collaboration with a machine. Complete manual labeling is even more expensive for the power industry because subject matter expertise is required to label many data, and crowdsourcing marketplaces, such as Amazon Marketplace, cannot be used to reduce the cost. On the other hand, AI can streamline the labeling task by detecting anomalies (so that the experts need to label only the nonconforming data) or by clustering data in categories (so that the human can label one data point per cluster).

Role of AI Experts

Most of the pioneering companies in AI are not in the power industry, and they employ the majority of the AI experts. The existing applications of AI that are being deployed in the power industry are mostly borrowed solutions used elsewhere in other industries—for example, chatbots for customer interaction.

Indeed, we are suffering from a lack of AI experts who have an intimate knowledge of the power industry. To fill this gap, the electric industry needs to promote collaborations with AI communities and to make AI experts aware of the technology's potential in our industry. Combining the knowledge of industry subject matter experts with AI expertise will help create targeted and reliable solutions.

Data Privacy and Security

The data collected for AI technologies are meant to train models for a good purpose but can be used in ways that violate the privacy of the data owners. For instance, energy usage data can be collected and used to help residential customers be more energy-efficient and lower their bills. The same data can also be used to derive personal information, such as occupancy and the religion of the residents. Worker digitization is another data privacy concern; as AI technologies are being applied more broadly to ensure the safety of workers, more personnel are becoming concerned that their data could be used to track their behavior at work or for other purposes unrelated to safety. Moreover, on the security side, data associated with many grid assets are prone to security concerns; therefore, access to and usage of the data requires strict controls.

Ethics

Along with privacy concerns the subject of ethics has been receiving significant attention in the field of AI recently, to the extent that companies and governments are forming advisory groups around this subject.

AI ethics can cover many areas. However, ethical concerns crop up most frequently in regard to fairness and morality. Many of the AI technologies are trained on data that carry their own biases and lead to conclusions that are also unfair. A notable example is an AI-based recruiting tool that chose men over women because the historical data reflected a tradition of favoring men over women. Morality refers to whether AI should make critical decisions on behalf of humans. For instance, should the AI in a driverless car try to save a baby or the grandparent in a fatal crash?

The foregoing are two common concerns, but AI ethics covers many more areas. It is not yet clear what AI ethics would mean to the power industry, but given the regulated aspects of the power industry, ethics plays an important role in making sure that the collected data are reliable and that accountable models are developed.

The EPRI Benefit

As the engine of faster, smarter information models, AI has great potential to help the industry forecast, fine-tune, save money, improve safety, protect the environment, and move closer toward a digital grid. However, deeper integration of the technology will require stakeholders to invest in collecting, gathering, and labeling data.

Further, the industry must enlist the expertise of the AI community in tailoring algorithms to our specific needs. This includes defining better evaluation metrics and understanding how the algorithms work so that biases and flaws do not skew the solution.

Moreover, any application of AI in the power industry requires a trustworthy platform designed for the security and privacy of data so that a solution meant to serve a common good does not jeopardize the safety of the grid nor the privacy of its customers.

EPRI, as a trusted collaborator in the electric power industry, is committed to driving the integration of AI in the electric power industry. Combining industry data, its own subject matter expertise, and AI experts EPRI is working to bridge the gap between our industry and the AI community. Considering the challenges of application of AI in the power industry, EPRI is focusing on collecting and curating data, educating the AI community, and independently evaluating AI tools.

EPRI invites all industry stakeholders to collaborate with us in advancing these areas and harnessing the power of AI for the electric power industry.

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