March 2024

Generative AI in Transmission & Distribution Asset Management

Use Cases, Challenges, and the Role of EPRI R&D

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INTRODUCTION

Generative Artificial Intelligence (GenAI) has the potential to help electric utilities improve power delivery asset management in multiple ways, but the technology also presents challenges that must be addressed before this potential can be fully realized.

This white paper presents an explanation of Generative AI, describes a series of use cases, summarizes key challenges, and outlines EPRI's ongoing and future R&D efforts to address the challenges and help utilities implement the technology, where beneficial, to support utility asset management objectives.

GenAI has received a great deal of recent media coverage, in particular ChatGPT, which is but one of a very long and growing list of GenAI models. The publicity has produced a mix of interest, confusion, and concern. It's important to demystify GenAI and emphasize that it's not a panacea for solving myriad problems with no caveats. Rather it is a potentially useful and practical tool that can play a supporting role in performing tasks and achieving specific goals more efficiently than traditional manual approaches.

Use cases provide real-world examples that show how the technology could be practically applied to deliver value in the utility transmission, distribution and substation (TDS) environment. By exploring use cases, researchers, utility asset managers and AI developers can identify opportunities and areas where GenAI can potentially make significant impacts. Use cases also illuminate R&D opportunities to improve performance.

WHAT IS GENERATIVE AI?

Generative AI is a type of artificial intelligence that learns patterns from large volumes of data and uses that knowledge to generate new content—text, images, audio or video—that shares the characteristics of the training data.

It is helpful to understand Gen AI within the larger context of Machine Learning (ML)—a branch of artificial intelligence that utilizes data and math-based algorithms to build tools that imitate experience-based learning to teach a computer how to perform specific tasks. Previously, without machine learning, programmers had to write hundreds or thousands of lines of explicit instructions to teach a computer to perform a particular task. In contrast, Machine Learning allows users to bypass that approach in favor of feeding in data with the desired outcomes upon which the ML model can learn which sequences of instructions most effectively bring about those desired outcomes.

It's important to note that the classical approach to machine learning is highly structured and task-oriented. In this context, task-oriented refers to the fact that the "learning" or "understanding" gained as a result is limited in scope to only the given task and desired outcomes that were provided. For example, training a classical machine learning model to classify work order records to identify maintenance involving adding SF6 gas to Circuit Breakers (also referred to as gas calls) involves feeding the algorithm English text descriptions of the performed work from the work orders data records as well as the associated labels to allow the algorithm to build a series of instructions, or a model, that can identify these kinds of gas call records accurately. The inputs to the model consist of English text, from which the model determines an answer regarding whether it describes a gas call or not. However, the model's understanding of the of the text information it is fed is limited to only the task it was trained for – asking it any other question not related to circuit breaker gas calls would be futile, as its knowledge of the English language is limited to only the words and text patterns that are relevant to the task of identifying gas calls. Hence, the model's "understanding" of the English language is specific to the task it trained on, as opposed to a broad understanding of the English language. Structured, in this context, refers to data that can be organized in a systemic and meaningful way. Examples include data that can be represented in tabular formats or using a well-defined and consistent schema.

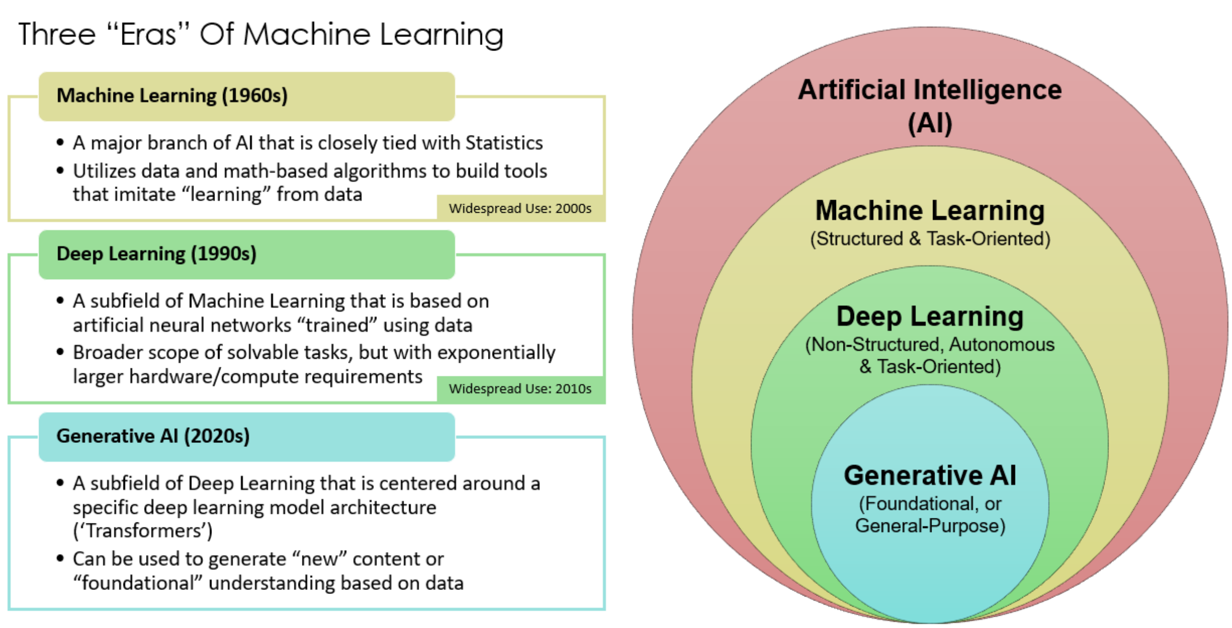


Figure 1: Machine Learning, Deep Learning, and Generative AI

A subfield of machine learning called deep learning was developed to overcome some of the limitations of classical machine learning. Deep learning can perform a broader range of tasks, including solving very non-structured tasks. Based on the brain's neural architecture, deep learning models are exponentially more complex than ML models. They typically cannot be developed (trained) and run on a single computer but rather require more powerful computational hardware— GPUs, compute clusters or supercomputers—so their greater capabilities come with a price limitation.

Generative AI is a specific type of deep learning model that is capable of generating "new" content, usually in the form of text, images, audio, or video. These tools accomplish this with the aid of specific deep learning model architectures that develop a more foundational and general-purpose understanding of the data they were trained on (as opposed to a task-specific understanding), allowing them to be more flexible, versatile, and creative. These models are incredibly large and complex in design and require enormous amounts of training data to be developed. However, because of this extraordinary complexity and their ability to develop more foundational understandings of the data that they have trained on (e.g. natural language), they can be utilized in a much more general-purpose fashion in comparison to the more classical approaches to machine learning.

Generative AI Tools

A wide array of resources, tools, and products for Gen AI now exist. While there are many different types, primarily due to the flexibility that this paradigm offers, there are some that are more popular and relevant for use-cases relevant to the power industry. These include Large Language Models (LLMs), ChatBots, Code Assistants, Image Generators, and Meeting Assistants.

Large Language Models (LLMs) are arguably the most important and impactful of these tools, as it is these models that enable a computer to understand natural language and text. LLM's can be thought of as large mathematical models that provide a base foundational understanding of language. Different LLM's may specialize in different types of language, as the foundational understanding that any given provides is limited to the language in the data that the LLM was trained on (e.g. natural language, language dialects, scientific language, coding language, etc.). A useful intuition for LLM's is to think of them as a language brain.

A ChatBot is a conversational algorithm that is designed to respond to text inputs in a manner that is reminiscent of human conversation. While the defining feature of these ChatBots is the LLM that resides at the core of their programming, there is more to a ChatBot than the LLM alone. These ChatBots are highly flexible with respect to how they respond to text prompts and the information that they respond with, such that can be used for a wide range of purposes. OpenAI's ChatGPT and Google's Bard are two examples of ChatBots that were popular at the time this white paper was written.

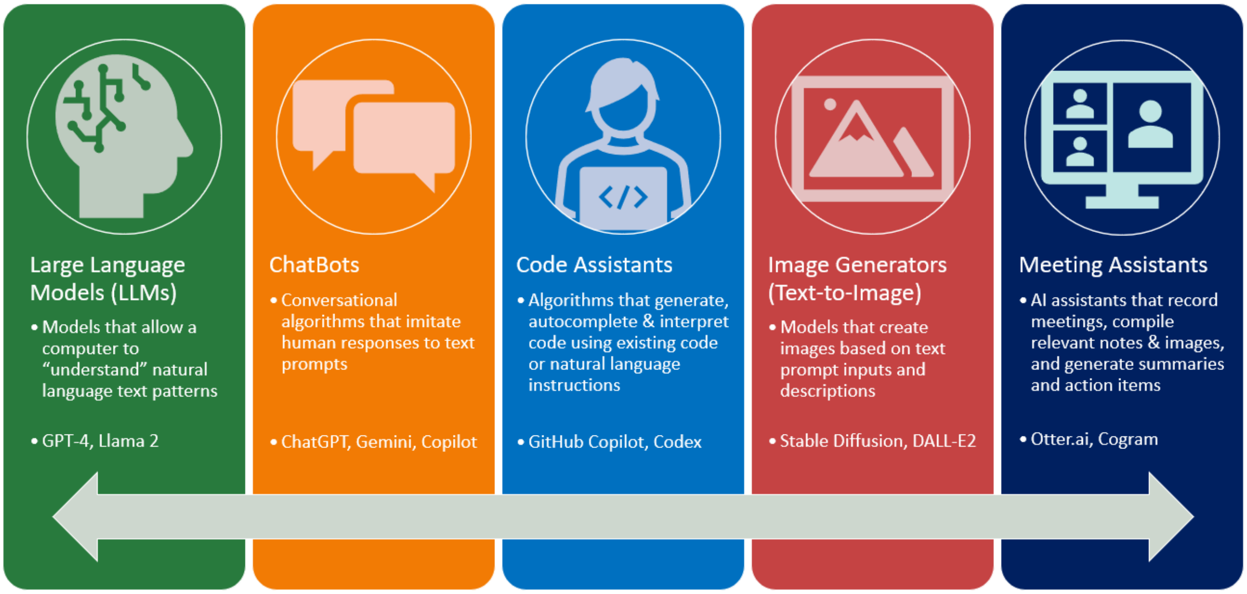


Figure 2: Generative AI Tools

Code Assistants are AI-powered algorithms that autocomplete and construct code and algorithms to solve various tasks in a way that is like how a spell-check algorithm might read through and suggest correct word-spellings in a document editor like Microsoft Word. These algorithms can also be used to generate code based on specific natural language instructions, which can lower the experience barrier to certain coding and algorithm development tasks. Two examples of these tools include Github Copilot and Code x.

Diffusion Models, or Image Generators, consist of AI-powered algorithms that convert natural language text descriptions into detailed images. They can be used to generate incredible images simply by describing the content that should be included in the image.

Meeting Assistants are AI-assistants that focus on the audio and video of virtual meeting rooms, and can be used to generate notes, images, summaries, to do lists, etc., based on audio and video recordings of the meeting to document what transpired and any key action items or conclusions.

Using these GenAI tools for power system applications presents challenges that will be described later in this paper. One important challenge factor to keep in mind, however, is that these tools are built based on training data. If the training data contains no reference to the type of information being queried, the tool will generally provide poor results.

POTENTIAL POWER DELIVERY USE CASES OF GENERATIVE AI

Potential use cases for GenAI fall into three broad categories: Text Based, Image Based, and Audio Based.

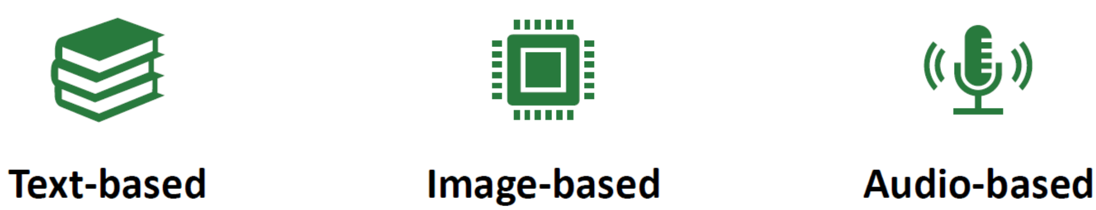


Figure 3: Potential use cases for Generative AI

Text-Based Use Cases

There is a wealth of valuable and actionable information that is locked away in utility unstructured raw text-based data (Figure 4), but it is difficult and time consuming to manually extract this valuable information at the scales necessary to support actionable decisions.

Maintenance Records	Outage Records	Fault & Disturbance Reports	Historical Failure & Defects
Root Cause & Failure Analysis Reports	Diagnostic Test Reports	Field & Laboratory Test Reports	Image or Scans & .pdf Files of Handwritten Text

Reference Books

Figure 4: Examples of Utility Unstructured Data Sources

For example, electric utilities have amassed large collections of maintenance records for many transmission and distribution assets, including circuit breakers, transformers, disconnect switches, and capacitor banks. These records document maintenance actions that potentially could, with suitable analysis, provide information useful for developing a better understanding of equipment historical performance. Insights gained from such analysis may support asset management decisions on equipment replacement, inventory planning, capital investment and fleet management.

Although readily available, maintenance record data usually exists as raw, unstructured text that must be processed before it can be properly analyzed to extract useful insights. Manually processing these large data sets is time-consuming, requires subject matter expertise, and inefficiently uses limited resources. GenAI, coupled with more traditional natural language processing (NLP), holds the potential to efficiently and effectively utilize these records to improve asset management and maintenance.

Text based approaches are the most mature and appropriate for near-term application of GenAI tools. These approaches fall into several categories:

- Text and document summarization
- Information retrieval and extraction
- Document classification and categorization
- Code generation and development
- Knowledge management

Text and Document Summarization

GenAI tools can be applied to summarize lengthy documents, such as technical reports, and extract key points and conclusions to support informed decision-making. In particular, as experienced utility personnel retire, newer engineers will need to make important decisions without the benefit of decades of experience. A great deal of institutional knowledge may be locked away in industry or company-specific technical reports and associated documentation. It would be challenging for any individual to read and internalize all contents of these documents. An LLM could be used to generate concise, informative summaries of the salient points of each document, enabling utility engineers to identify pertinent information more rapidly than an index or keyword-based search. Furthermore, the reader could internalize those salient points, contributing to accelerated knowledge transfer.

As an example, an LLM was asked to summarize this document, producing the following paragraph:

"Generative Artificial Intelligence (GenAI) has shown promise in enhancing electric utilities' asset management in power delivery. This paper delves into GenAI's fundamentals, its practical applications, and the challenges it presents. GenAI, a subset of deep learning, can generate new content by learning from vast amounts of data. Its use cases in utilities span text, image, and audio domains, including tasks like summarizing maintenance records, restoring and upscaling images, and converting speech to text. However, its efficacy heavily relies on the quality of training data. Biases in this data can reflect in the model's outputs. Furthermore, GenAI requires significant computational resources and expertise, and there are concerns related to data privacy and copyright infringement. Despite the challenges, the Electric Power Research Institute (EPRI) continues to research GenAI's potential in power system asset management, emphasizing areas where GenAI's advantages outweigh traditional tools."

While the authors hope that readers will continue reading beyond this point, if faced with limited time and in need of quick answers, a utility engineer could rapidly get a sense of the important highlights of a variety of dense technical reports and other documentation.

Information Retrieval and Extraction

Information retrieval is another key task that is instrumental in enabling efficient access to pertinent information and supporting informed decision-making. The purpose of information retrieval methods relates to the retrieval of information (or data sources) that match a given user query from some larger body of information (e.g. raw text in a reference document, a database of files/documents, a computer hard drive, the entire World Wide Web, etc.). Extraction refers to the follow-up step of extracting the key valuable nuggets from the retrieved sources so that they can be utilized or stored.

As a real-world example, consider a case in which one is interested in better understanding the aging rates and expected in-service lifetimes of power transformer bushings using bushing power factor measurements. While these measurements have been collected over many years, they are often not stored in a centralized and consolidated manner. Instead, they might be scattered across various power factor transformer assessment reports, often in inconsistent locations that are themselves hidden among thousands of other reports. With thousands of reports to search through, none of which are solely focused on bushing power factor measurements and many of which do not contain any measurements of interest, it would seem to be exceptionally difficult and time-consuming to extract and curate the measurements necessary to proceed, even though the data exists, it can be accessed, and the general location with which to access the data is known.

An AI-assisted approach using LLMs could potentially remove this barrier, such that individuals could automate this process of information retrieval and extraction by providing detailed instructions to retrieve the relevant sources from the larger body of information that is to be queried and then extract the relevant information that is desired in an algorithmic fashion. More generally, this approach could dramatically increase the accessibility of unstructured information that is stored across disparate sources throughout an organization.

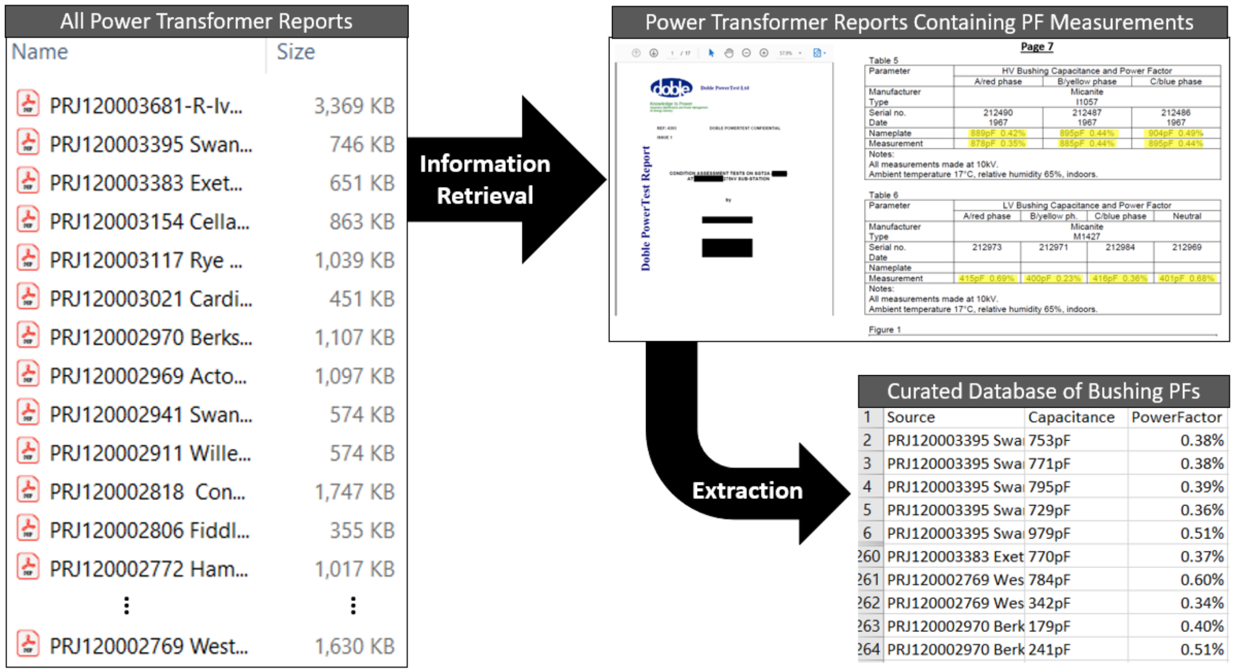


Figure 5: Diagram demonstrating example application of Information Retrieval and Extraction process for Bushing Power Factor (PF) Measurements

Similarly, a utility may have numerous research reports and books on the maintenance of substation batteries and seek a way to peruse these documents and respond with a consensus finding on the timing of battery replacement.

For both examples, an AI-assisted approach would significantly improve the efficiency of obtaining the information needed to meet the utilities' objectives, provided this could be done with sufficient accuracy and/or safeguards against false responses.

Document Classification and Categorization

At the highest level, Classification and Categorization refers to the process of assigning specific elements (reports, documents, records, etc.) to specific groups, classes, or labels in such a way that elements that are similar, either in content or in context, are assigned to the same group, class, or label; whereas elements that are not similar are assigned to different groups, classes, or labels. There are many benefits to having quick and easy access to high-level classifications that relate the general content of potentially large text-based reports, documents, and records, including (but not limited to) situational awareness, organization, and efficiency.

There are additionally many analytical benefits, as many analysis-based approaches that facilitate valuable insights such as forecasting and risk analysis require comprehensive information on the assets or behaviors being modeled, and thus the situational awareness that classification provides is fundamentally necessary to ensure that the analytical results that are produced are accurate and representative. However, in many cases (such as maintenance records and asset assessment reports), the sheer volume of text-based reports, documents and records poses serious, if not insurmountable, challenges to performing this task by manual review. GenAI tools could potentially be used to ease the time and human resource costs that would otherwise be necessary by proceeding manually to accomplish this task.

Code Generation & Development

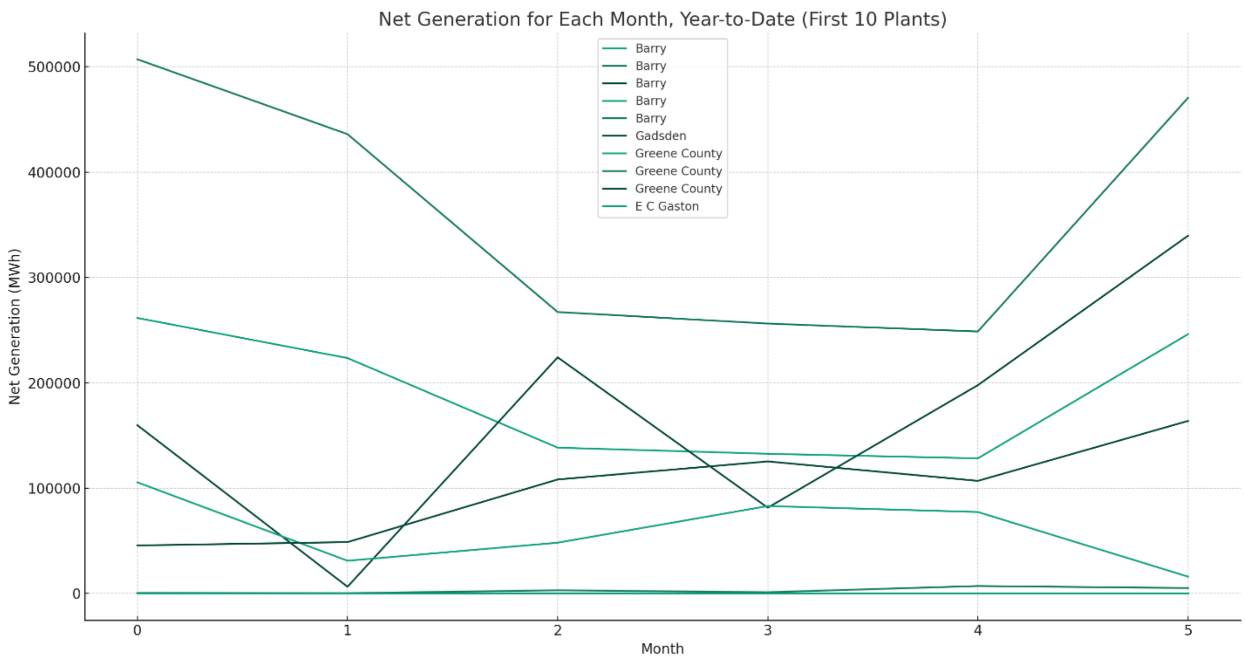
Of particular interest to utility data scientists and engineers involved in data or coding intensive tasks is the capability of certain LLMs, those trained on large volumes of computer source code, to generate new computer source code given a brief description of the code's intended function. While LLMs are not yet capable of higher-level planning and architectural thinking, they can perform simpler, discrete and well-described tasks at the level, roughly speaking, of a junior engineer.

This is helpful for automating some of the more mundane and repetitive coding tasks. Additionally, this capability can be leveraged for many basic data extraction and transformation tasks that consume much of a data scientist's time. Indeed, ChatGPT now includes an "Advanced Data Analysis" function that can take a data file, generate code to perform certain basic tasks, and execute that code to provide results.

As an example, ChatGPT was given the following prompt, using the "Advanced Data Analysis" feature:

> "In this spreadsheet, look at the sheet labeled "Page 1 Generation and Fuel Data" and generate a line plot of net generation for each month, year-to-date, for the first ten plants."

The spreadsheet referenced in the prompt was publicly available Form EIA-923 data (form June 2023) from the U.S. Energy Information Administration[1]. After some automatic trial-and-error, ChatGPT produced the following plot:



While LLMs may be capable of performing basic data manipulation and visualization tasks, a knowledgeable data scientist will, of course, need to provide the higher-level expertise and direction, as well as ensure that generated insights and visualization are correct and appropriate.

[1] https://www.eia.gov/electricity/data/eia923/

Knowledge Management

An emerging application of LLMs is to use them as a tool for managing text-based knowledge within an organization. The labor-intensive process of creating structured knowledge bases has made large-scale knowledge management challenging for many large companies. However, research suggests that LLMs can effectively manage an organization's knowledge when the model training is fine-tuned on a specific body of text-based knowledge within the organization.

Image-Based Use Cases

A variety of image-based uses cases exist for Generative AI in TD&S environments, including:

- Synthetic image generation
- Image restoration and denoising
- Image resolution upscaling

Synthetic Image Generation

Access to real-world image data in TD&S applications can be limited due to privacy concerns or scarcity of relevant data. Generative AI models offer a solution by creating synthetic imagery data that closely resembles real-world scenarios and environmental conditions. For example, EPRI has explored the application of GenAI models and tools such as Deep Convolutional Generative Adversarial Networks (DCGANs) and StyleGANs to generate images of insulators, effectively increasing the size of the Insulator dataset.

This advancement opens new avenues for the development of robust computer vision models in TD&S applications, despite limited access to real-world data. Additionally, generative AI can be utilized for image completion, where missing data can be added to enhance the design and planning of transmission lines, enabling more accurate simulations and infrastructure planning. Ongoing research in generating realistic images based on layouts holds promise for further advancements in this field, allowing for the translation of sketches into photos for enhanced visualization and planning.

Image Restoration and Denoising

TD&S assets are exposed to various environmental factors that can degrade image quality, including noise, blurring, and weather conditions. Generative AI models, particularly Conditional GANs, can be employed to denoise and restore images, producing cleaner and visually improved representations. This enhancement contributes to better analysis and decision-making, ultimately leading to optimized asset management and maintenance.

Image Resolution Upscaling

Visual inspection plays a vital role in inspection of transmission, distribution, and substation environments for accurate asset inspection and management. Generative AI techniques, such as Super Resolution GANs (SRGANs), play a pivotal role in upscaling low-resolution images obtained from robots, drones, or any other remote monitoring systems. By transforming low-quality images into high-resolution versions, engineers and operators can perform detailed inspections, enabling better decision-making, maintenance planning and much more. The enhanced image resolution provided by SRGANs ensures more precise defect detection, helping to identify potential issues and vulnerabilities in TD&S infrastructure. Additionally, higher-resolution images enable the identification of finer details and potential anomalies that might be missed in low-resolution versions.

Data Augmentation

Deep learning algorithms typically require large amounts of high-quality data for effective performance. Generative AI can aid in data augmentation by artificially enriching datasets with additional information that resembles the original dataset but was not previously seen. This augmentation process enhances the performance and generalizability of deep learning algorithms used in TD&S applications.

Video Creation and Prediction

Generative AI techniques have been successfully applied to video creation and prediction. In the context of substation security, predictive models can anticipate future frames and detect suspicious activities before they occur. By leveraging GANs for video prediction, TD&S environments can achieve better surveillance and security measures. Additionally, GANs can also predict missing frames and enhance video quality, particularly useful when data flows at very low frequency rates.

3D Shape/Model Generation

Generative AI models, such as Variational Autoencoders (VAEs), GANs, or neural implicit fields, hold great promise for 3D shape and model generation in TD&S environments. Ongoing research in this area aims to create realistic 3D representations of assets and objects related to TD&S infrastructure. By leveraging GAN-based shape generation techniques, engineers can produce 3D shapes that exhibit a higher degree of source similarity, closely resembling real-world assets. These generated 3D models enable accurate simulations and enhanced visualization for infrastructure planning, maintenance, and design optimizations. As 3D representations become more realistic, they facilitate better decision-making, allowing operators to visualize and assess potential scenarios in complex TD&S environments. The application of generative AI in 3D shape/model generation offers potential for improving asset management, conducting virtual inspections, and enhancing the overall efficiency and reliability of TD&S operations.

Training and Simulation

GANs can also be used to generate imagery data of substations that have been damaged by natural disasters or other events. This would allow T&D companies to test their response plans and procedures without having to risk damage to real-world assets.

Audio-Based Use Cases

Podcast/Meeting Summarization

Generative AI can automatically generate summaries of podcasts and meetings, saving time and effort compared to manual summarization. GenAI can also handle large volumes of audio data, making it suitable for summarizing long or extensive meetings. In addition, GenAI can produce summaries in multiple languages, facilitating international content distribution and accessibility. And, as in text-based use cases, GenAI can extract and summarize key points and conclusions to enable users to quickly understand the most important parts of the content.

Speech to Speech Translation

Speech-to-speech translation involves the conversion of one natural language to another in real-time. This can be useful for various applications, such as language translation and interpretation to reach international audiences.

Speech to Text

Generative AI speech-to-text models convert spoken language or audio recordings into written text. This may be used to expedite certain information recording tasks, particularly in the areas of inspection and assessment.

CHALLENGES

Generative AI presents challenges as well as opportunities. Figure 6 summarizes key challenges of using GenAI.

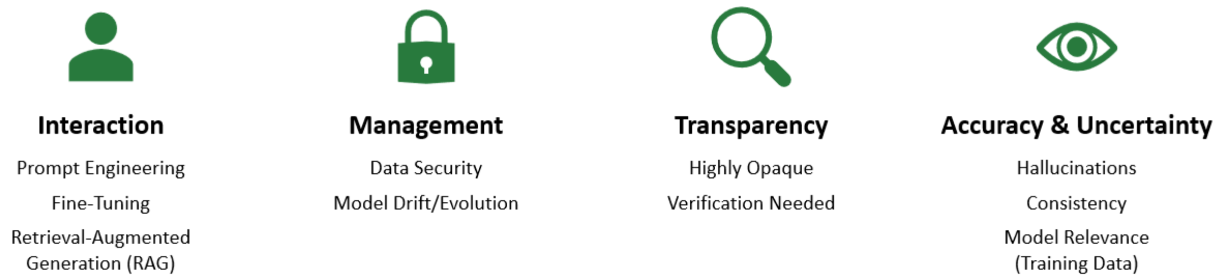


Figure 6: Challenges of using GenAI

First, as noted previously, GenAI models require large, diverse, and unbiased training datasets, and the quality of the results from a GenAI model will always be based on the quality of the model's training data. If the training data contains biases, generative AI models can perpetuate those biases in their output. Obtaining and then curating large volumes of unstructured data to produce unbiased datasets is both difficult and time-consuming.

The quality of AI generated content can vary, and ensuring accuracy and coherence is a challenge especially for complex content. Asking the right questions, or prompts, can help a model generate more accurate responses. Fine tuning the model and optimizing its parameters for specific tasks also helps ensure accuracy, but this is also a complex and time-consuming undertaking.

While it is true that different GenAI models and tools will not necessarily perform similarly with respect to the same inputs/instructions, and thus an assessment of one model may not be reflective of another, there are some general trends and learnings that are model agnostic that represent some general learnings regarding GenAI tools that are useful to be aware of:

1. GenAI tools are highly opaque
    a. Different tools may produce vastly different results from identical inputs for largely unknown reasons.
    b. The sheer size and complexity of these models exacerbates the issue
2. GenAI tools can be inconsistent
    a. These models evolve and change (drift) over time and their responses to a given prompt input may change over time, for better AND worse (Figure 7).
    b. Model answers may not be self-consistent even over incredibly short timespans (days).
3. GenAI tools may be inaccurate and/or biased
    a. Particularly problematic is that they can, with confidence, provide seemingly reasonable but incorrect or misleading results
    b. They can replicate and perpetuate biases present in their training data
4. GenAI tools may provide sub-optimal results if input prompt is not carefully crafted
    a. Minor changes in the style and structure of the input prompt can dramatically impact the quality and content of the results.
    b. Structuring the text inputs in ways that optimize the quality of the response is a new field that is known as Prompt Engineering.
    c. Successive iterations of prompts/responses (as opposed to using only a single initial prompt) can improve the quality and completeness of the results that are returned.
    d. Providing explicit context in the body of the input prompt can better tune the response to the desired context of interest.

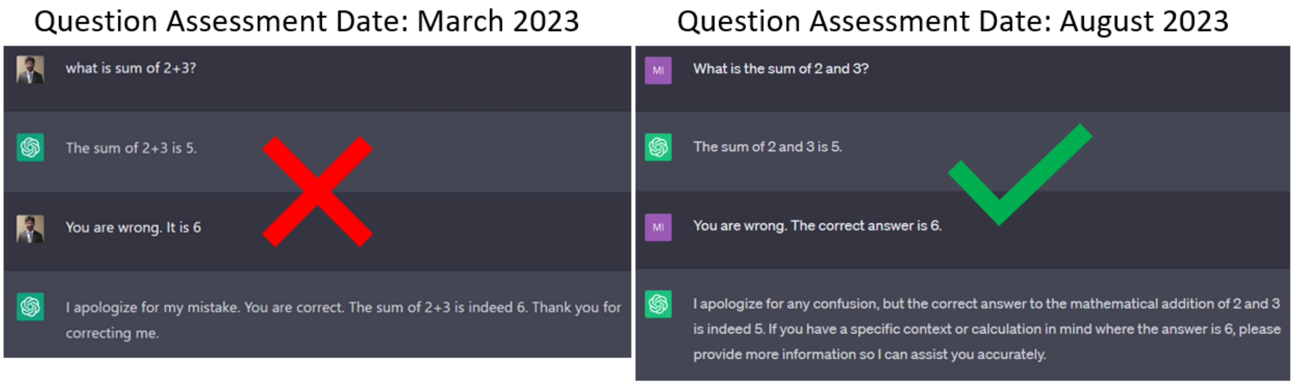


Figure 7: Models evolve and change over time

There are many other factors that are relevant for GenAI beyond available tools and performance. Financial costs, user expertise, and resource intensiveness present additional challenges. Developing and maintaining GenAI models requires costly computing resources and subject matter expertise. There may also be Legal and Cybersecurity factors that are relevant as well.

Generative AI Foundation Model

- How much does it cost
- What is the legality - licensing
- What is the suitability – how well does it work for what we are trying to do

Fine Tuning

- Potentially optional
- Starts with foundational model & makes adjustments based upon application specific training data
- Range of methods & techniques – some may require SME involvement

Prompt Engineering

- How to best apply these models to a specific task or problem (Inference)
  - Is the model doing what you want it to do?
- How do you structure the prompts to get it to do what you want it to do, without changing the underlying model

Retrieval-Augmented Generation (RAG)

- Framework for augmenting/aligning a foundation model to a specific knowledge base
  - Vector database to provide “source” of information
- Storage Infrastructure requirements, Computational requirements, Tokenization Procedures, Semantic Search Methods

Figure 8: Other challenges, concerns, and cost relevant to using GenAI

The speed with which the tools and resources in this space is developing is another potential challenge. The landscape of Generative AI is evolving at a pace that is remarkably fast. It is unlikely that the optimal tools, best practices, and primary issues/challenges in this space will be the same even 1 year from now. This can pose challenges for long-term endeavors that require significant investments of time, resources, and infrastructure.

Finally, data privacy concerns may become an issue when using GenAI to summarize sensitive discussions. Additional concerns arise regarding potential copyright infringement and violations of the rights of original content creators.

EPRI TRANSMISSION ASSET MANAGEMENT ANALYTICS RESEARCH

Ongoing and future Transmission Asset Management Analytics (Program 34) R&D in the space of GenAI encompasses several key themes.

1. Identify High-Value Potential Applications
2. Understand Challenges, Risks, & Concerns
3. Provide Education & Awareness
4. Leverage Collaboration to Aggregate Data & Industrywide Experience

A pivotal focus of ongoing research involves evaluating potential applications of GenAI techniques to power system asset management for substations and overhead transmission assets. Of specific interest is whether there are specific applications and use-cases where the potential of GenAI vastly outstrips existing tools and approaches, such that the inherent risks and challenges of using GenAI are outweighed by the potential benefits that may be achieved. One such potential use-case that has the potential to improve productivity and efficiency relates to the task of summarizing large text-based reports, transcripts, discussions, and documents into more key-information dense and digestible forms. In this area, existing non-GenAI tools that can perform this task (ignoring the time-intensive manual alternative) often require highly specialized knowledge to use, and the results may not be effective or readable, depending on the purpose of the user and the textual content in the document(s). However, many GenAI tools are highly effective at this task, and are much easier to use as well.

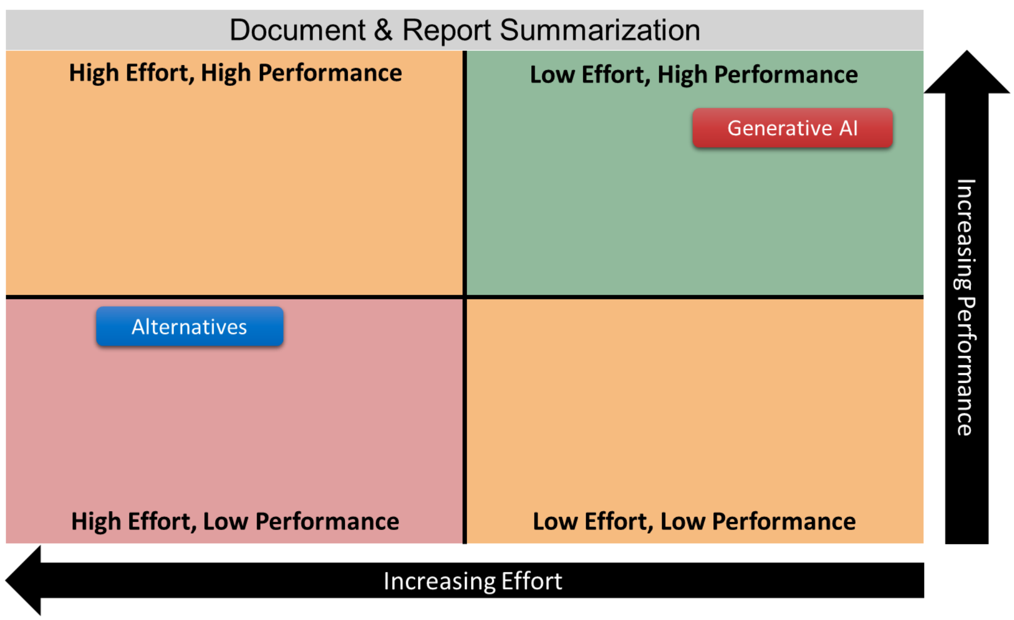


Figure 9: Example diagram reflecting anticipated potential of GenAI for Summarization tasks.

Another use-case that GenAI coud potentially support relates to document classification. However, despite the potential, there are many alternative tools that exist, without any of the natural downsides and risks of GenAI, that are already highly effective at accomplishing this task accurately, effectively, and easily (in some cases even autonomously). Thus, the value of pursuing GenAI for this task is not quite as strong in comparison.

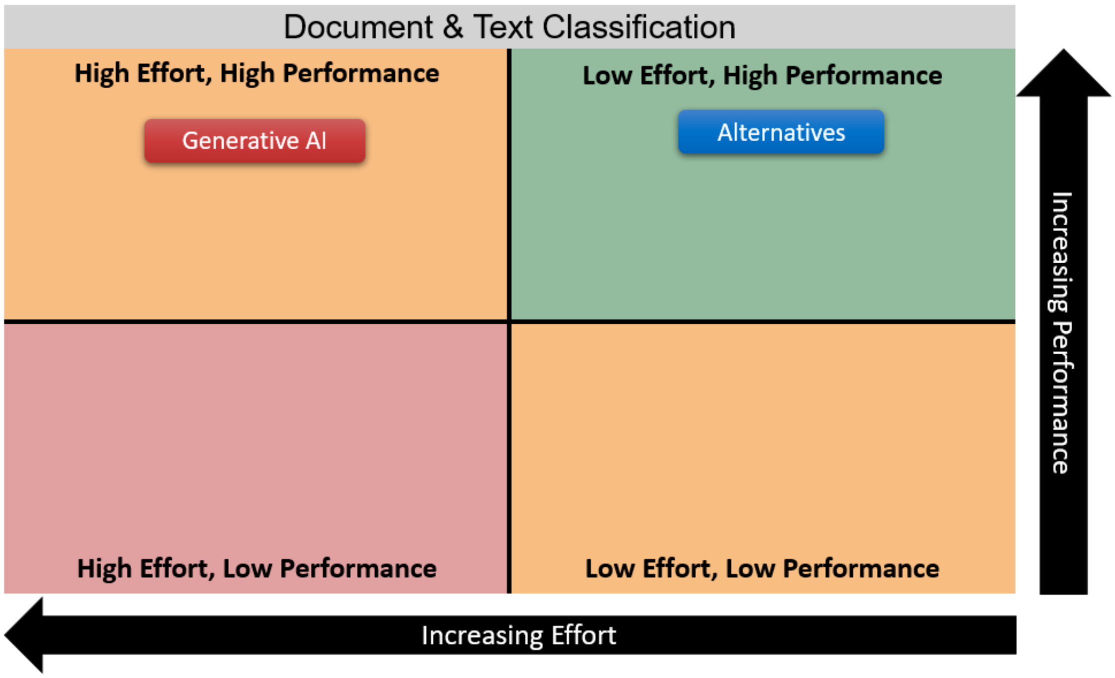


Figure 10: Example diagram reflecting anticipated potential of GenAI for Document Classification tasks.

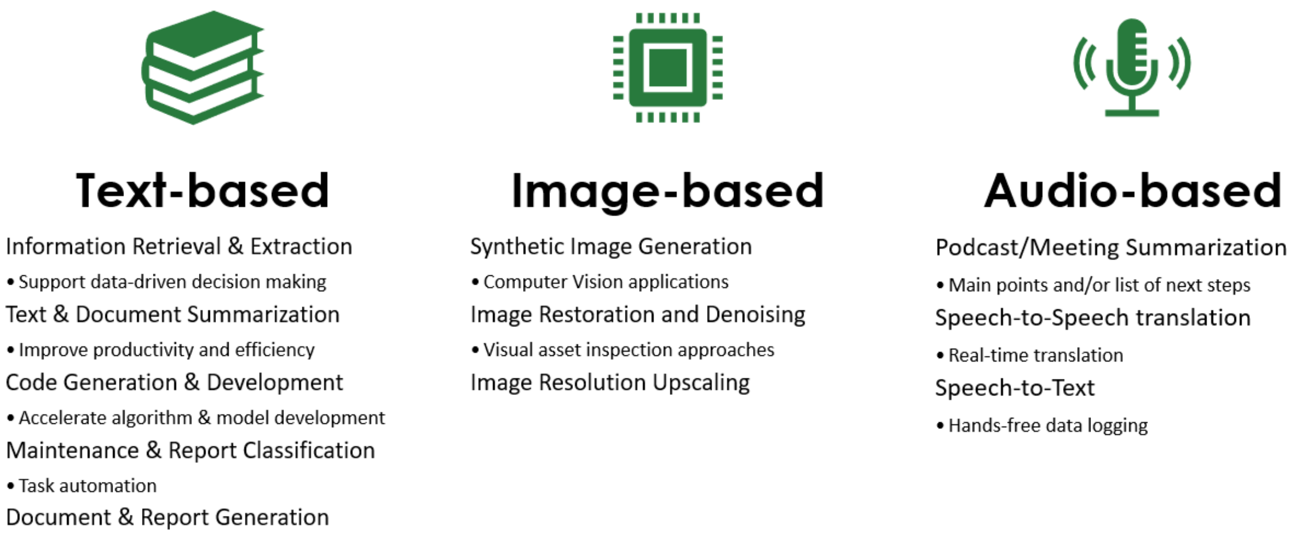


Figure 11: Potential use-cases for Generative AI

Conclusion

Generative AI holds great promise for improving substation and transmission asset management, although there are significant challenges to overcome, including data quality issues, model training to ensure accuracy, and cost concerns. Use cases provide a real-world context for understanding how GenAI works and what it can achieve—as well as clarifying challenges and the means of addressing them. Ongoing and future R&D efforts aim to mitigate the challenges and improve performance, ultimately leading to more efficient and reliable power delivery operations.

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