

Leveraging AI and ML Tools in the Utility Industry for Disruption Avoidance and Disaster Recovery

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Abstract: The utility industry is facing increasing disruptions due to climate change, aging infrastructure, and cyber threats. To enhance operational resilience and disaster recovery, utilities leverage Artificial Intelligence (AI) and Machine Learning (ML) technologies. These tools enable predictive maintenance, anomaly detection, and real-time decision-making, allowing for the anticipation of failures and a faster crisis response. Case studies from companies such as Avangrid and PRASA highlight the practical benefits of AI and ML in reducing outages, optimizing resource allocation, and minimizing recovery time. As the utility sector continues to adopt these advanced technologies, the potential for cost savings, improved customer satisfaction, and enhanced service reliability has become more apparent. AI and ML are key to ensuring a more resilient and efficient future for utilities, particularly in the face of increasing environmental and cyber threats.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Utility industry, Disruption avoidance, Disaster recovery, Predictive maintenance, Anomaly detection, Resilience, Operational efficiency, Real-time decision-making

1. Introduction

The utility industry has a rich history of integrating emerging technologies to bolster resilience, efficiency, and reliability. Over the decades, these advancements have shifted from manual monitoring systems to sophisticated automation and data-driven decision-making processes. Initially, utilities incorporated technologies like Supervisory Control and Data Acquisition (SCADA) systems, which allowed operators to remotely monitor and control equipment, enhancing operational visibility and reducing manual intervention. Later, Geographic Information Systems (GIS) and digital mapping tools enabled precise resource tracking and spatial analysis, supporting both preventive and reactive measures in infrastructure management.

By the 1990s, utilities began adopting predictive maintenance technologies, incorporating basic analytics to monitor asset health and predict equipment failures. These systems, however, relied heavily on rule-based algorithms and historical data, which limited their ability to adapt to rapidly changing conditions. As environmental challenges and infrastructure complexities increased, it became clear that

traditional methods, while foundational, were no longer sufficient to address the growing demands of the industry.

In recent years, the utility sector has turned to advanced technologies, notably Artificial Intelligence (AI) and Machine Learning (ML), to bridge these gaps and meet modern challenges head-on. These tools provide capabilities beyond traditional automation, enabling real-time data analysis, complex predictive modeling, and rapid decision-making. AI-driven predictive maintenance, for example, goes beyond simple rule-based systems by analyzing diverse data sources—such as sensor readings, weather patterns, and usage history—to detect early signs of equipment failure with a high degree of accuracy. This proactive approach minimizes costly downtimes, improves resource allocation, and ensures service reliability.

During natural disasters or emergencies, AI and ML algorithms can synthesize massive volumes of data to provide actionable insights for recovery efforts. Real-time AI analytics can coordinate response teams, prioritize repairs, and optimize logistics, significantly reducing the time required to restore services. For instance, during hurricanes

or wildfires, AI models can predict which areas are most vulnerable, allowing utilities to pre-position resources and prepare contingency plans.

The financial implications of disruptions underscore the urgency of adopting these advanced technologies. Studies show that power outages can cost utilities as much as \$1 million per hour in lost revenue and restoration expenses, while in the U.S., annual losses from outages are estimated at \$150 billion (Pandey et al., 2023). Extreme weather events are also increasing, with 22 climate disasters in 2022 alone each incurring over \$1 billion in damages (Pandey et al., 2023). By leveraging AI and ML tools, the utility industry can not only improve resilience but also enhance public safety and service continuity in an era of unprecedented challenges.

2. Criticality of Avoiding Disruptions and Efficient Recovery

Avoiding disruptions in utility services is paramount to maintaining operational stability, customer satisfaction, and financial performance. Utility disruptions, whether due to natural disasters, equipment failures, or cyberattacks, can lead to prolonged outages, economic losses, and damage to the provider's reputation. For example, it is estimated that the U.S. utility sector faces losses amounting to billions of dollars annually due to unforeseen disruptions (Federico et al., 2022). This highlights the need to adopt advanced technologies to mitigate risks and ensure efficient recovery.

Efficient recovery mechanisms are equally critical, as prolonged outages not only impact customer satisfaction, but also incur regulatory penalties. On an average, utility companies take hours to days to recover from major disruptions. Regulatory bodies often require utilities to restore power within specified timelines, with penalties imposed on non-compliance (Cao, 2023). The pressure to maintain service continuity is compounded by the financial implications of service disruptions because delayed recovery can result in substantial financial losses.

Technology plays a pivotal role in reducing the frequency and severity of disruptions. Traditional recovery systems rely on human intervention and manual processes, often resulting in longer recovery times. However, with the integration of AI and ML tools, utility companies can now predict potential disruptions, optimize grid management, and automate disaster recovery efforts (Sun et al., 2020). These technologies enable the analysis of large datasets in real time, allowing utilities to anticipate failures and respond more swiftly, thereby reducing the average recovery time from

days to hours in some cases (Production-Ready and Resilient Disaster Recovery for DLT Pipelines, 2023).

As AI and ML continue to evolve, their impact on the utility industry is expected to be transformative. Predictive maintenance algorithms powered by ML can help identify potential system failures before they occur, allowing utilities to address issues proactively. Similarly, AI-driven disaster recovery solutions provide more efficient and resilient responses to both physical and cyber threats. This shift toward AI-enhanced recovery systems is expected not only to reduce recovery times, but also to minimize the operational and financial impacts of disruptions, ensuring that utility companies remain compliant with regulatory requirements while maintaining high customer satisfaction (Deepika, 2019; Ibrahim, 2019).

3. Impact of Disruptions and Recovery Delays

Disruptions in the utility industry can lead to severe financial and operational consequences, with substantial costs associated with lost revenue, restoration efforts, and customer dissatisfaction. According to a study by S&P Global Market Intelligence, each major outage can cost utilities up to \$1 million per hour in lost revenue and restoration costs (Deloitte Switzerland, 2017). Beyond direct financial losses, prolonged outages can damage a utility provider's reputation and erode customer trust. Studies indicate that frequent or extended outages can lead to a 15-20% decrease in customer satisfaction, which impacts customer retention and can lead to regulatory scrutiny (Utility Dive, 2023).

The impact of disruptions extends beyond financial loss. Prolonged outages can lead to public safety issues, particularly during extreme weather events, when access to essential services is critical. A study by the Deloitte Center for Energy Solutions found that the average duration of power outages in the U.S. has increased by 59% over the past decade, with the average customer experiencing more than eight hours of outages per year (KPMG, 2016).

3.1. Reasons for Disruptions

Disruptions in the utility industry arise from various factors, each of which presents unique challenges. Extreme weather events such as hurricanes, wildfires, and other natural disasters can cause significant damage to critical infrastructure, leading to widespread outages (Deloitte Switzerland, 2017). Additionally, an aging infrastructure poses a serious risk because many utility systems operate well beyond their intended lifespan, increasing the likelihood of failures and service interruptions (Guest, 2021). Cyber threats

also contribute to disruptions, with malicious actors targeting utility systems, potentially leading to both outages and data breaches. Moreover, equipment failures, whether due to malfunctions or outdated technology, can result in localized outages and service interruptions. Each of these factors underscores the importance of building resilient systems in the utility industry.

Case Study: Hurricane Maria in Puerto Rico

In 2017, Hurricane Maria devastated Puerto Rico's power grid, leaving the island without electricity. It took nearly a year to restore power to all customers, with the recovery effort costing an estimated \$3.2 billion (Rivera, 2017). The prolonged outage had severe consequences for the local economy and public health, highlighting the need for improved resilience and recovery capabilities in the utility sector.

Analysis

The data clearly demonstrates the significant financial and operational impact of disruptions in the utility industry. Inadequate disruption management and recovery efforts can lead to substantial losses, reputational damage, and public safety risks. To mitigate these risks and ensure reliable service delivery utilities must prioritize investments in resilient infrastructure, advanced analytics, and emergency response capabilities.

By leveraging AI and ML technologies, utilities can enhance their ability to predict, prevent, and respond to disruptions more effectively. Predictive maintenance powered by AI can help identify equipment anomalies before they lead to failures, whereas real-time analytics can facilitate faster decision-making during crises. By investing in these technologies, utilities can minimize the frequency and duration of outages, ultimately reducing the financial and operational impact of disruptions.

4. AI and ML Techniques for Disruption Avoidance and Disaster Recovery

4.1. Overview of AI and ML Techniques

In the utility industry, Artificial Intelligence (AI) and Machine Learning (ML) are increasingly used to enhance operational efficiency and improve resilience against disruptions. Several key techniques include the following.

Smart Grid Management:

AI and ML are essential in managing smart grids by optimizing energy distribution, predicting demand, and dynamically adjusting resources based on real-time data.

These technologies enable utilities to maintain a balanced grid, prevent overloads, and respond quickly to fluctuations, which is crucial for ensuring service reliability and efficiency.

Energy Consumption Forecasting:

ML models analyze historical data and patterns to accurately forecast energy demand, allowing utilities to better allocate resources and avoid wastage. This technique is particularly valuable for predicting peak load periods, ensuring efficient energy use, and supporting sustainable energy practices.

Fraud Detection:

AI-driven anomaly detection techniques help utilities identify unusual patterns in consumption data that may indicate fraudulent activity, such as energy theft or meter tampering. These tools allow utilities to quickly detect and address fraud, safeguarding revenue and protecting the integrity of the system.

Predictive Maintenance:

AI models analyze historical and real-time data to predict equipment failures before they occur, thereby allowing for preventive measures and minimizing downtime. This is particularly important for reducing the operational impact of equipment failures in critical infrastructure such as power grids (Chaouachi et al., 2012).

Anomaly Detection:

Machine Learning (ML) algorithms play a crucial role in anomaly detection within the utility industry by continuously monitoring data streams from sensors, IoT devices, and other systems. Through unsupervised learning techniques, such as clustering and Principal Component Analysis (PCA), ML models learn the normal patterns of system behavior and identify deviations that may indicate potential disruptions. Advanced techniques like autoencoders and recurrent neural networks (RNNs) can be employed to capture complex temporal patterns and detect subtle anomalies in time-series data, which are often early indicators of issues like cyberattacks or equipment malfunctions.

By leveraging statistical and probabilistic models, such as Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM), utilities can detect anomalies with greater accuracy and distinguish between normal fluctuations and actual threats. These systems operate in real-time, allowing utilities to detect and respond to issues promptly, thereby reducing the risk of larger failures and improving response times (Ibrahim, 2019). Additionally, the use of ensemble methods, which combine multiple algorithms, enhances the robustness of anomaly detection by providing diverse perspectives on the same data, further bolstering the utility's resilience against disruptions.

Optimization Algorithms:

AI-driven optimization algorithms are essential in managing energy distribution and load balancing in the utility industry. Techniques like Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) are frequently used to optimize resource allocation and minimize operational costs while adhering to regulatory constraints. Additionally, heuristic algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), help utilities manage complex, non-linear optimization problems in real-time, allowing for dynamic load balancing and efficient resource utilization. More advanced algorithms, including Deep Reinforcement Learning (DRL) and Model Predictive Control (MPC), can

learn and adapt to changing demand patterns and environmental conditions, enabling utilities to proactively prevent overloads and anticipate system stress points. These approaches allow utility companies to mitigate risks, ensure faster recovery from unforeseen disruptions, and ultimately enhance service reliability (Cao, 2023).

4.2. Architectures and Frameworks

Implementing AI and ML solutions in the utility industry requires sophisticated architectures and frameworks to facilitate seamless data flow, model training, and deployment. A common approach involves the use of cloud-based platforms that support large-scale data processing and model execution, ensuring high availability and resilience during disruptions.

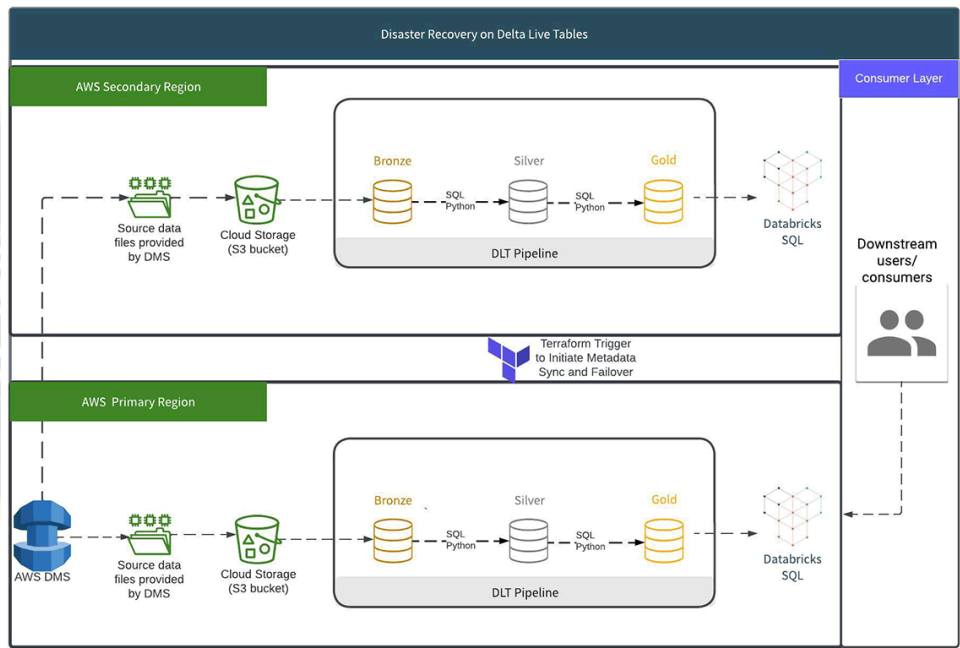


Figure 1: Disaster Recovery Architecture, Source: (Production-Ready and Resilient Disaster Recovery for DLT Pipelines, 2023)

The diagram above illustrates a disaster recovery architecture for **Delta Live Tables (DLT)** pipelines in a cloud environment, demonstrating a dual-region setup leveraging AWS services. The **primary region** processes source data through AWS Database Migration Service (DMS) and stores it in Amazon S3. A DLT pipeline processes the data in three stages, Bronze, Silver, and Gold, each representing increasingly refined data, which is then consumed by downstream users via Databricks SQL. In the event of a disruption in the primary region, a failure in the **secondary region** is triggered by Terraform, which ensures the synchronization of metadata and continuous data processing through the secondary pipeline, thus ensuring uninterrupted

service (Production-Ready and Resilient Disaster Recovery for DLT Pipelines, 2023).

This architecture supports **predictive maintenance** and **anomaly detection** by integrating ML models within the data pipeline. These models continuously learn from historical data (Bronze and Silver layers) and apply insights into real-time data (Gold layer) to predict failures or detect anomalies. In addition, AI-driven optimization algorithms help streamline data processing and improve the system performance during high demand or after failure.

5. Case Studies of Successful AI and ML Applications

5.1. Case Study 1: Predictive Maintenance in Power Grids

Avangrid

Avangrid, a leading sustainable energy company, has integrated AI and machine learning into its power grid management to improve reliability and efficiency across its subsidiaries, such as Central Maine Power and New York State Electric & Gas (Winston, 2023). The company spearheaded several key projects, including the "Predictive Health Analytics" initiative, which uses AI algorithms to monitor sensor data from the grid. By detecting patterns that suggest equipment degradation, the system allows predictive maintenance, thereby preventing failures before they occur (Winston, 2023). GeoMesh, which is another initiative, employs advanced mapping techniques that analyze millions of data points, such as weather conditions, vegetation density, and historical outage records, to predict performance issues related to environmental factors (Winston, 2023).

Additionally, Avangrid's "HealthAI" project utilizes photographic systems to assess the condition of critical infrastructure such as poles and wires. By identifying vulnerabilities early, a company can address potential risks before they cause outages (Winston, 2023). Through these AI-powered initiatives, Avangrid has significantly enhanced grid reliability and operational efficiency, estimating that retail electricity providers could save as much as \$3 per megawatt hour by adopting these advanced AI tools, further proving the economic benefits of these innovations (Winston, 2023).

5.2. Case Study 2: Disaster Recovery Optimization in Water Utilities

Puerto Rico Aqueduct and Sewer Authority (PRASA)

In the aftermath of Hurricane Maria in 2017, the Puerto Rico Aqueduct and Sewer Authority (PRASA) encountered significant challenges in re-establishing water services across the island, with the recovery efforts lasting nearly a year (Rivera, 2017). This prolonged recovery underscored the necessity for a more resilient disaster recovery strategy. In response, a collaborative effort between researchers from the University of Puerto Rico and the University of Illinois at Urbana-Champaign led to the development of an AI-based optimization framework designed to streamline and enhance the disaster recovery process (Bvazquez, 2018).

The AI framework utilized machine learning algorithms to predict potential damage to the water infrastructure by analyzing both historical data and real-time sensor

information. This capability has allowed PRASA to take more targeted and preventative measures during recovery operations (Bvazquez, 2018). Additionally, the system optimized the allocation of personnel, equipment, and materials, ensuring that resources were deployed effectively where they were most needed.

6. Benefits of AI and ML Investment for Utility Companies

6.1. Enhanced Resilience

AI and ML technologies have significantly enhanced resilience against disruptions and disasters in the utility sector. For example, the National Grid in the UK and Southern Company in the U.S. utilize AI for predictive maintenance to monitor power grid health and detect faults before failures occur. These systems improve operational resilience by identifying potential issues early on and reducing the frequency and impact of outages (Cao, 2023). Furthermore, Pacific Gas and Electric (PG&E) in California has employed AI in their disaster recovery strategies to mitigate wildfire risks by prioritizing resource allocation and optimizing response measures (Sun et al., 2020).

6.2. Cost Savings and Efficiency

AI and ML have driven cost savings and operational efficiency across leading utility companies. Duke Energy in the U.S. reported a 25% reduction in downtime and a 15% decrease in operational costs owing to AI-powered predictive maintenance solutions (Federico et al., 2022). Similarly, Électricité de France (EDF) has leveraged AI for more precise load forecasting, optimizing electricity generation and reducing excess production, leading to notable cost reductions for both companies and consumers (Deepika, 2019). This efficiency in demand-response management enables utilities to better balance supply and demand, ultimately lowering peak demand costs.

6.3. Improved Customer Service

AI has improved customer service experiences in several leading utility companies. Enel in Italy and Iberdrola in Spain deployed AI-powered chatbots to handle customer inquiries, significantly reducing response times and enhancing customer satisfaction (Chaouachi et al., 2012). These chatbots assist with billing queries, outage reports, and provide real-time service updates. Furthermore, Iberdrola employed machine learning to offer personalized energy-saving recommendations based on customer usage patterns, improve engagement and foster a more positive customer relationship (Federico et al., 2022).

6.4. Future Use Cases

The future of AI and ML in utilities has several exciting possibilities. One area with significant potential is real-time grid optimization, in which AI algorithms dynamically adjust power flow in response to supply and demand fluctuations. Siemens and Tesla Energy are already exploring solutions in this area, although high costs and the need for more advanced hardware remain challenges (IBRAHIM, 2019). Another promising use case is AI-driven decentralized energy management, particularly as microgrids have become more prevalent. Finally, AI-integrated energy storage systems, which help manage and balance renewable energy, are gaining attention as the sector moves toward sustainable energy sources (Federico et al., 2022).

7. Solution Providers & Collaboration

In recent years, AI and ML solution providers have developed an array of specialized tools for the utility industry, helping companies to modernize operations, optimize resources, and enhance disaster resilience. Key cloud providers like Azure, AWS, and Google Cloud Platform (GCP) offer robust AI and ML solutions that are tailored for utility use cases, from predictive maintenance to load management.

Microsoft Azure:

Azure offers a suite of AI and ML tools for the utility industry, including *Azure Machine Learning* for building, training, and deploying predictive models, and *Azure IoT Hub* for real-time data ingestion from sensors. Azure's *Digital Twins* platform enables utilities to create virtual models of physical assets, which are instrumental in monitoring system performance and detecting anomalies before they escalate into major issues. Additionally, *Azure Synapse Analytics* supports data integration and analysis, allowing utilities to make data-driven decisions at scale.

Amazon Web Services (AWS):

AWS provides specialized services such as *Amazon SageMaker*, which enables utilities to build and deploy ML models for applications like demand forecasting and anomaly detection. *AWS IoT Core* integrates with various IoT devices and sensors for data streaming, while *AWS Lambda* offers serverless computing for real-time event processing. AWS's *QuickSight* provides data visualization and reporting, helping utility companies monitor KPIs and quickly address operational challenges.

Google Cloud Platform (GCP):

GCP's tools for the utility industry include *BigQuery*, a powerful data warehouse for storing and analyzing large datasets, and *Vertex AI*, which offers end-to-end model development and deployment capabilities. GCP also provides

AutoML, which allows utilities to create custom ML models without extensive coding, making it accessible for companies with limited ML expertise. Additionally, *Google Earth Engine* aids in geospatial analysis, which can be valuable for managing and monitoring utility infrastructure across vast geographic areas.

These platforms provide utilities with scalable and customizable solutions, enabling them to leverage AI and ML for efficient resource management, improved resilience, and enhanced operational efficiency.

Collaborative Expert Groups and Technical Communities

Collaboration within technical communities is essential for advancing AI and ML applications in the utility industry. These expert groups bring together professionals to share insights, best practices, and research findings, helping the industry to innovate and overcome shared challenges.

Utility Analytics Institute (UAI):

UAI is a prominent community dedicated to advancing analytics in the utility sector. UAI hosts regular conferences, webinars, and forums where members share case studies, technical insights, and lessons learned. The organization publishes industry reports and benchmarks on topics like predictive analytics, grid optimization, and customer data management. By fostering collaboration among members, UAI helps utility companies accelerate their adoption of AI and ML tools and implement data-driven strategies.

IEEE Power & Energy Society (PES):

IEEE PES is a global community of experts in electric power and energy. The society focuses on technical education, research, and the development of standards, contributing significantly to AI and ML advancements in utilities. IEEE PES regularly publishes research papers and organizes conferences, such as the IEEE PES General Meeting, where professionals present their latest findings on AI-driven innovations in power systems. Their working groups and committees are instrumental in defining best practices and developing new standards for AI-based grid management and disaster recovery in the utility sector.

These communities play a critical role in the development and adoption of AI and ML in utilities, creating a platform for sharing insights and promoting best practices that benefit the entire industry.

8. Conclusion

The integration of AI and ML tools in the utility industry has immense transformative potential, significantly improving resilience, disruption avoidance, and disaster recovery. By

leveraging advanced analytics, predictive maintenance, anomaly detection, and real-time optimization, utilities can anticipate and mitigate operational risks more efficiently than ever before. These technologies not only enhance service reliability but also drive cost savings, improve customer service, and ensure faster recovery from disruptions, thereby reducing the financial and operational impacts on utilities.

Moreover, the increasing frequency of extreme weather events and cyber threats necessitates the adoption of advanced technologies to safeguard critical infrastructure and maintain service continuity. As AI and ML continue to evolve, the future promises even more innovative applications such as real-time grid optimization and decentralized energy management. To remain competitive and resilient in the face of growing challenges, utility companies must prioritize investments in AI and ML, positioning themselves to meet current demands and future disruptions.

References

1. Bvazquez. (2018, March 2). Thursday, March 1, 2018 (Puerto Rico) | CEE 449 International Collaborative Design Projects - University of Illinois at Urbana-Champaign. Illinois.edu. <https://publish.illinois.edu/cee449-sgwi/2018/03/01/thursday-march-1-2018-puerto-rico/>
2. Cao, L. (2023). AI and data science for smart emergency, crisis and disaster resilience. *International Journal of Data Science and Analytics*, 15(3), 231–246. <https://doi.org/10.1007/s41060-023-00393-w>
3. Chaouachi, A., Kamel, R. M., Andoulsi, R., & Nagasaka, K. (2012). Multiobjective intelligent energy management for a microgrid. *IEEE transactions on Industrial Electronics*, 60(4), 1688-1699.
4. Deepika, M. (2019). AI & ML-Powering the Agents of Automation. BPB Publications.
5. Deloitte Switzerland. (2017, June 19). Disruption in the power and utilities sector. Deloitte. <https://www2.deloitte.com/ch/en/pages/energy-and-resources/articles/disrupt-power-utilities.html>
6. Federico, L., Doerr, H., Wilson, A., Fontanella, L., Lehmann, J., Hlinka, M., & O'Reilly, J. (2022, November 7). The big picture: What's the U.S. utility sector facing in 2023 and beyond? S&P Global Market Intelligence. <https://www.spglobal.com/marketintelligence/en/news-insights/blog/the-big-picture-what-s-the-u-s-utility-sector-facing-in-2023-and-beyond>
7. Guest, S. (2021, June 24). SAP BrandVoice: The Utilities Industry Is At The Center Of A Massive Global Shift. Forbes. <https://www.forbes.com/sites/sap/2021/06/23/the-utilities-industry-is-at-the-center-of-a-massive-global-shift/>
8. IBRAHIM, A. (2019). The Cyber Frontier: AI and ML in Next-Gen Threat Detection.
9. KPMG. (2016, September). No going back: Five disruptive trends reshaping the utilities sector. Retrieved from <https://assets.kpmg.com/content/dam/kpmg/tr/pdf/2017/01/No-going-back-five-disruptive-trends-reshaping-the-utilities-sector-Sep16a.pdf>
10. Lacey, S. (2014, September 2). The Meaning of Disruption: How Should Utilities Think About Change? Greentechmedia.com; Greentech Media. <https://www.greentechmedia.com/articles/read/How-Should-Utilities-Think-About-Disruption>
11. Pandey, U., Pathak, A., Kumar, A., & Mondal, S. (2023). Applications of artificial intelligence in power system operation, control and planning: a review. *Clean Energy*, 7(6), 1199–1218. <https://doi.org/10.1093/ce/zkad061>
12. Production-Ready and Resilient Disaster Recovery for DLT Pipelines. (2023). Databricks. <https://www.databricks.com/blog/2023/03/17/productio-n-ready-and-resilient-disaster-recovery-dlt-pipelines.html>
13. Rivera, E. (2017). USACE teams with PRASA to provide water to 100,000 residents, businesses in NW Puerto Rico. DVIDS. <https://www.dvidshub.net/news/254055/usace-teams-with-prasa-provide-water-100000-residents-businesses-nw-puerto-rico>
14. Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. *Natural Hazards*, 103(3), 2631–2689. <https://doi.org/10.1007/s11069-020-04124-3>
15. Winston, K. (2023, August 28). Avangrid launches AI team to leverage data, anticipate future grid challenges. Spglobal.com; S&P Global Commodity Insights. <https://www.spglobal.com/commodityinsights/pt/market-insights/latest-news/electric-power/082823-avangrid-launches-ai-team-to-leverage-data-anticipate-future-grid-challenges>
16. Atri P. (2023, November). Mitigating Downstream Disruptions: A Future-Oriented Approach to Data Pipeline Dependency Management with the GCS File Dependency Monitor. *J Artif Intell Mach Learn & Data*

Sci 2023, 1(4), 635-637. DOI: doi.org/10.51219/JAIMLD/preyaa-atri/163

17. Utility Dive. (2023, March 27). Strategies to improve business customer satisfaction for utilities. Retrieved from <https://www.utilitydive.com/spons/strategies-to-improve-business-customer-satisfaction-for-utilities/645251/>

