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Original Article

Applying Generative AI in Predictive Maintenance: A New Paradigm

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Abstract: *Predictive maintenance (PdM) is an essential component of modern industrial operations, especially with the fourth Industrial Revolution (Industry 4.0). Traditional PdM relies on either rule-based algorithms or deep learning neural nets to predict downtimes, increasing uptime and productivity. Traditional PdM faces a lot of challenges owing to lack of sufficient high-quality data, leading to a high number of false positives. With the recent advancements in generative AI (GenAI) a new set of enablers have come forward which can enable higher quality PdM models enabled through advanced simulations and synthetic data generation. This paper highlights applications in manufacturing, transportation and energy, showcasing how the integration of GenAI with existing PdM frameworks can help unlock performance and ease adoption of these models. We also discuss specific applications of Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Transformers in PdM.*

Keywords: *Artificial Intelligence, Generative AI, Industry 4.0, Machine Learning, PdM, Predictive Maintenance, Operations Improvements, GenAI*

I. INTRODUCTION

A. Predictive Maintenance (PdM):

There are various approaches to equipment maintenance

a) Reactive maintenance:

only solves the issue when the system breaks down or malfunctions. The malfunction becomes apparent, and then the repairing steps are applied.

b) Planned maintenance:

is previously scheduled to perform regular inspections and maintenance tasks at predetermined intervals to prolong the system's life and reduce repair costs, regardless of whether the system has shown failure signs.

c) Predictive maintenance (PdM):

PdM is a critical component of the Fourth Industrial Revolution (Industry 4. 0) and will change the way heavy industries manage their assets through sensors, releasing multi-billions of dollars in potential cost savings and/or productivity improvements. By accurately estimating when a piece of equipment might fail (this could be a wind turbine, robotic arms, heavy duty excavators etc.), predictive maintenance can reduce downtime, making it a superior approach compared to reactive or planned maintenance which have historically been used in the industry. Traditional PdM approaches rely on data on historical failures and supervised machine learning models trained on sensor data. While these methods have proven to be effective, they face multiple challenges not limited to incomplete datasets due to low amount of data archived, low data quality, and the inability to predict rare or unseen failure events given the supervised nature of the training.

Predictive maintenance helps reduce downtime at a fraction of the cost of planned maintenance, especially as it does not need any equipment downtime for diagnosis. However, PdM often suffers from a high number of false alarms (false positive rates) owing to lack of high-quality data, or failure to predict rare equipment failures (false negatives).

B. Generative AI (GenAI):

GenAI refers to deep-learning models that can generate high-quality, close to real text, image, audio, video content based on the large amounts of data they were trained on. Such models have also demonstrated promise in generating high quality synthetic data and helping simulate complex un-seen scenarios. It has emerged as a solution to some of the challenges with PdM we outlined earlier, with models capable of generating high quality synthetic data.

Generative AI(GenAI) can transform the applicability of PdM by introducing synthetic data generation techniques, superior anomaly detection, and simulations of hypothetical failure scenarios. By doing this GenAI can enhance predictive

accuracy, providing a more reliable approach to PdM, one which is not inundated with false positives. This paper explores these novel trends and discusses the role of GenAI in PdM of the future.
Key techniques include:
a) Generative Adversarial Networks (GANs):

GANs are composed of two opposing networks—the generator and the discriminator—trained in tandem in an adversarial process to produce realistic synthetic data.

b) Variational Autoencoders (VAEs):

VAEs are generative models that encode the data into a compressed latent representation, which allows for anomaly detection and the generation of high-quality synthetic data.

c) Transformers:

Transformers are popular in time-series analysis because they are able to model dependencies across long sequences of sensor data, which is great for predictive maintenance (PdM).

II. APPLICATIONS OF GENAI IN PREDICTIVE MAINTENANCE

A. Synthetic Data Generation for PdM:

One of the major problems with applying PdM in real world scenario is that there isn't enough failure data, even if one has decades of archived data, especially for equipment that doesn't fail very often or is very costly when it does. Generative AI, and GANs in particular, attempt to remedy this by generating large amounts of good fake data to augment the few real failure cases. Wang et al. proved that GANs can produce believable sensor data of these unlikely failure occurrences in industrial equipment, thus improving the training sets of predictive models. This artificial data allows for better generalization of the model, which in turn makes the failure predictions much more dependable.

A few examples of applications of GANs for synthetic data generation

- Lu, Du et al (2022) proposed a propose an improved Generative Adversarial Networks (GANs) named MSGAN with the adaptive update strategy mechanism based on WGAN-GP to generate fake anomaly samples, improving anomaly detection accuracy on real robotic sensor datasets.
- Losi et al (2024) developed a GAN model to create synthetic data for long term forecast of a gas turbine operation, and showcased that the predictive power of a model is lower by 2.5% in the case of long term prediction compared to the synthetic data.
- Tse et al (2024) introduced a novel application of Generative Adversarial Networks (GANs) in the creation of a digital twin of a semiconductor manufacturing plant.

B. Anomaly Detection via VAEs:

Anomaly detection on sensor data is the first step to failure prediction in PdM, because anomalous data are "canaries in a coal mine. VAEs are really good at this because they can learn what is normal for the machinery and then when it starts to do something abnormal (i.e., about to fail) the VAE will be able to detect that.
A few examples of applications of Auto encoders for anomaly detection for asset uptime:

- Jakubowski et al (2022) presented how unsupervised learning using a variational autoencoder may be used to monitor the wear of rolls in a hot strip mill, a part of a steel-making site.
- Alfeo et al (2020) showcased the use of an autoencoder in the design of an anomaly detector for smart manufacturing.

C. Time-Series Forecasting with Transformers:

Deep learning models have long been used to observe degradation or predicting failure ahead of the occurrence of the component or asset. In a review of 106 papers on deep learning–driven approaches five architectures are popularly applied in predictive maintenance- RNNs, CNNs, fully connected deep neural networks, stacked encoders and deep belief networks. Transformer models, originally developed for natural language processing, have recently seen some adaption for time-series analysis due to their ability to capture long-term dependencies.

Nascimento et al (2022) proposed the development and evaluation of an automatic fault classifier model for PdM based on a modified version of the Transformer architecture, namely T4PdM, to identify multiple types of faults in rotating machinery and reported overall accuracy of 99.98% and 98% for MaFaulDa and CWRU public databases.
Research on the application of Transformers in PdM is still new, but will hopefully unlock additional ways to improve performance and reduce false positives.

III. INDUSTRY APPLICATIONS

Predictive Maintenance has been an essential ingredient to boost productivity across a range of industries, especially in those with heavy reliance on equipment, machinery and infrastructure.

A. Smart Manufacturing:

For years now sensors have been in use in factories to monitor the state of the machinery, with alarms constantly going off and clicking away in the control room. GenAI will be able to generate synthetic failure scenarios and enhance anomaly detection in real time. Earlier in this paper we shared few examples for robotic manufacturing, semiconductor plant, steel making site.

B. Energy Sector:

Wind and gas turbines are generally in remote locations, so if something breaks, it takes forever and costs a lot to get it fixed, as there are no technicians sitting around to fix things. Also, if we only get to an asset after it breaks, it could lead to catastrophic failure. The energy sector has always been a key industry leveraging PdM, and has been using GenAI powered PdM applications already. Earlier in this paper we discussed use of GAN model to create synthetic data for long term forecast of a gas turbine operation.

C. Transportation and Fleet Management:

PdM is very important in the logistics and transportation industry, in order to reduce fleet downtime. This has been used in a broad range of fleets ranging from ships (Yigin et al (2024) using leveraging GANs to predict failures) to aircraft (Reddy et al (2016) using autoencoders) to haul trucks. Many of these examples used GANs to generate a more accurate forecasting of vehicle maintenance, thus increasing fleet utilization and decreased costs.

IV. CHALLENGES AND FUTURE DIRECTION

GenAI really is revolutionary a technology and its application in PdM especially so, however, there are some challenges that will need to be overcome in order to facilitate large scale use.

A. Data Privacy and Security:

GenAI is very promising in PdM but there is still the issue of data privacy and security. And real data synthesis must make sure that no one can recreate or leak out any sensitive operational data that could possibly give others a competitive edge. Right security policies must be in place to ensure that the asset data is not leaving the asset's private network unless explicitly allowed.

B. Model Interpretability:

Generative models, especially GANs and VAEs, are often criticized for their lack of interpretability, which can limit their adoption in PdM. Future research should be done on developing explainable AI methods that allow maintenance engineers to see the logic behind a model's predictions.

C. Integration with Industrial IoT:

The integration of GenAI with Industrial Internet of Things (IIoT) systems poses technical challenges, particularly in terms of real-time data processing and latency. The future will require edge computing and real-time AI systems to take full advantage of GenAI in PdM. It will be even more so with wide spread adoption, because "on the cloud" data processing will be looked down upon as a risk by many organizations performing critical processes.

D. Cost of building PdM Solutions:

Building PdM solutions comes with its costs, and may now in the right economic choice for smaller organizations or low value assets. In use cases where full scale supervised PdM solution may yet not be economic, less data intensive methods such as anomaly detection maybe a successful first step. They may be faster to implement and much more efficient with application of VAEs as we discussed, but come with lower predictive power.

V. CONCLUSION

Generative AI is already revolutionizing the world of predictive maintenance by helping resolve common data challenges like low volume or quality/variety of data by generating synthetic data, enhancing anomaly detection, and application of novel deep learning architectures. GenAI enhances the robustness of PdM models, enabling better decision-making and reducing operational costs, especially in critical industries like manufacturing, power generation among others. However, challenges like privacy, interpretability, IIoT integration and costs have to be addressed to allow widespread adoption. The future of PdM lies in using Generative AI techniques, and will allow industries to leverage PdM at scale, unlocking the next frontier of performance.

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