SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/https://doi.org/10.14445/23488379/IJEEE-V12I12P111

Volume 12 Issue 12, 140-150, December 2025

Original Article

Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins for Explainable Wind Turbine Fault Diagnosis

Surendar Aravindhan[1*], M. Shyamalagowri[2], J.Karthika[3], Rajan.C[4]

[1]*Department of Pharmacy, Saveetha University, Chennai, Tamilnadu, India.*
[2]*Department of EEE, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India.*
[3]*Department of Science and Technology Research Analyst, Advanced Scientific Research, Salem, Tamilnadu, India.*
[4]*Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning),*
K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India.

[*]*Corresponding Author : surendararavindhan@ieee.org*

Received: 07 October 2025 Revised: 09 November 2025 Accepted: 11 December 2025 Published: 27 December 2025

Abstract - *Wind Turbine Generators (WTGs) are considered one of the essential elements in the renewable energy system. Despite this, due to the complex, non-linear, coupled nature of fault dynamics, fault detection of WTG poses enough challenge. Conventional signal processing, model-based estimation, and machine learning fault diagnosis methods provide valuable insights, but have limitations in prediction, scalability, comprehensibility, and uncertainty. New hybrid frameworks relying on techniques like deep learning fused with fuzzy decision support help enhance the detection of harmonics and condition-based optimization of control devices. Unfortunately, these various advanced methods are currently missing under-utilized capabilities that focus on explainable, reasonable, and proactive prediction of the fault's progressive harm—a paper framework for advanced fault diagnosis and predictive maintenance of Wind Turbine Generators (WTGs). To begin, the turbine's dynamics are embedded into adaptive digital twins using physics-informed neural networks that develop self-evolving micro-digital twins at the component level (rotor, gearbox, bearings, stator). Secondly, the neuromorphic spiking Graph Neural Networks (S-GNNs) will extract temporal transients from multiple vibration, current, and rotor speed signals while integrating causal inference for root-cause analysis and counterfactual reasoning. The system combines micro-twin predictions with causal learning of neuromorphic to provide estimates of fault intensity, RUL, and interpretable decision support. This technique will provide improved accuracy of fault diagnosis, real-time deployment on edge devices using voltage-efficient neuromorphic computing, uncertainty calibration of RUL prediction, and operator trust using transparent causal explanations. Through the unification of physics-informed modeling, neuromorphic efficiency, and causal AI, this work sets the groundwork for the next generation of explainable and sustainable fault diagnosis in wind turbine generators.*

Keywords - *Wind Turbine Fault Diagnosis, Neuromorphic Computing, Causal AI, Physics-Informed Micro-Twins, Predictive Maintenance.*

1. Introduction

With the world's transition into renewable energy, wind power has established itself as a significant source of sustainable electricity. The International Energy Agency has estimated that in the coming years, wind power will become significant. The stability and effectiveness of the Wind Turbine Generators (WTGs) are critical to the stability of the grid and the reduction of the Levelized Cost Of Energy (LCOE) in this growing sector. Wind turbine generators (WTGs) are complex non-hydraulic machines. They work on unpredictable aerodynamic forces and loads. Besides, they perform in conditions of high environmental stress. This exposes them to the failures of vital components of the drive train. These components are generators, gearboxes, and bearings. Rotor winding degradation, eccentricity, bearing wear, and gearbox failures remain among the most frequent reasons for unplanned downtime. They can cause prolonged outages, costly repairs, and massive losses in production, particularly in offshore installations whose maintenance logistics are challenging. The standard methods of fault diagnosis include Fast Fourier Transform (FFT), Wavelet Transform (WT), Hilbert-Huang Transform (HHT), and Empirical Mode Decomposition (EMD), which have been employed in the analysis of vibration, current, and acoustic signals based on fault signatures. However, its methods are susceptible to noise, and they have difficulties in handling non-stationary signals; they fail to predict the propagation of the fault. Model-based techniques such as equivalent circuit representation, state observers, and state-space models are very interpretable. They are limited by the fact that they rely on correct models of turbines.

Additionally, they lack dexterity in various working conditions. The advent of machine learning systems in different fields of application drives an information-based method of classification, like Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) Architectures. All of these exhibit strong classification accuracy and automate feature extraction. However, they are “black-box” in nature, require massive labelled datasets, and hardly ever provide uncertainty estimates or causal reasoning. Several hybrid frameworks have emerged. This is generally related to deep learning and fuzzy support for decision-making. They aim to integrate pattern recognition and rules-based decision-making. However, they remain largely reactive processes. The subjective design of rules is a big concern. Likewise, they lack predictive or causal insight in real-world decision-making. Even though research on deep learning, fuzzy-logic diagnostics, and digital-twin models to monitor the health of wind turbines has been conducted, available solutions have a number of shortcomings. The existing models of data analysis are less capable of causal reasoning, and most of them cannot generalize to different conditions of operation. Methods based on digital twins offer physical interpretation, which is usually computationally intensive and challenging to implement at the turbine edge. Besides, the majority of hybrid frameworks do not concurrently solve the fault detection, fault-intensity estimation, Remaining Useful Life (RUL) prediction, and causal explanation problems in a single framework. These shortcomings underscore the importance of having an explainable, energy-efficient, and physics-consistent framework that could prognosticate in real-time in a distributed wind energy system. The CNGL-PiMT framework proposed presents the distinctive combination of physics-informed micro-twin modelling, event-driven neuromorphic graph learning, and causal inference as the complete wind turbine prognostics. Contrary to the current methods of deep learning and digital-twin, CNGL-PiMT processes diagnostic, prognostic, and causal-explanation tasks into one computational pipeline. The neuromorphic implementation is highly energy-efficient in inference and has high diagnostic accuracy, and the causal graph formulation is easy to understand, and the reasoning is operator-explicable. Compared to the performance of the DL-fuzzy and FL-dt, there is an earlier error of fault detection, a reduced error of RUL prediction, and a significantly higher energy efficiency.

2. Literature Review

The WTG condition monitoring has followed a developmental path in four major methodological waves, including signal processing, model-based estimation, data-driven learning, and hybrid/digital-twin systems. Having taken all of this into account, nothing at the moment manages to predict faults in terms of Remaining Useful Life (RUL), causally interpretable, and energy-efficient inference in real-time. The classical techniques of signal processing, such as the Fast Fourier Transform (FFT), Wavelet Transform (WT), Hilbert–Huang Transform (HHT), and Empirical Mode Decomposition (EMD) and its variants, such as CEEMDAN, etc., are still essential for extracting spectral sidebands and transient features from vibration and current signals. However, these methods cannot appropriately handle signals that change with time; they are susceptible to noise and do not possess good prognostic capability, thus limiting long-term fault prediction [2, 4, 18, 19, 26]. Two model-based strategies include state-space representations, observer design, and Kalman particle filtering techniques, which are physically interpretable since they compare a measured system with an expected system. In spite of the fact that these models are based on the first principles, they may come out poorly when parameters are not well determined, and models are not calibrated. They tend to be fragile and operationally irregular and can be disturbed by the environment, and they are difficult to maintain in large heterogeneous groups of turbines [1, 7, 17, 27]. The recent emergence of machine learning algorithms, including SVMs, CNNs, LSTMs, and autoencoders, has made feature extraction automated, thereby revolutionizing fault detection and significantly improving accuracy, similar to process activity data. However, data-driven models require the capacity of supercomputers. They also require the presence of strong training data. On the whole, they are not very explainable and are referred to as black boxes. They also lack mechanisms for good uncertainty quantification and cause-and-effect reasoning, which are crucial for operator trust and decision reliability [20, 22-24]. Recent trends in hybrid systems have sought to integrate physics-based knowledge and data-driven intelligence. Such approaches as Deep Learning with fuzzy decision support, federated learning to improve distributed model training, and modelling digital twins to replicate virtual turbines have led to considerable enhancements in all instances. These techniques, however, come with new limitations. Federated models are, however, based on elaborate opaque backbones of deep learning, and monolithic digital twin models are slow to evolve with changes in turbines[10, 11, 12, 14, 16, 21]. The progress in Artificial Intelligence has created numerous new directions for explainable and efficient condition monitoring. Paraphrase this (21 words): Causal AI has possibilities for counterfactual reasoning and root-cause attribution, so it allows systems to infer how changes in operational conditions impact fault development. At the same time, neuromorphic computing, namely through spiking neural networks, allows for event-driven, low-power processing, which can enable real-time deployment at the edge of the turbine [5, 6, 13]. Recent studies have shown that the connection within the turbine can be learned using spiking Graph Neural Networks.

They build the topology of the turbines. The use of PINNs also helps in embedding physical laws into the learning and thus improves reliability and generalization [5, 9, 25]. The past studies related to wind turbine fault diagnosis cover statistical signal-processing techniques, deep neural networks, fuzzy rule-based systems, and digital-twin modelling. Data-driven schemes have excellent detection performance but very low interpretability and sensitivity to changes in operating conditions. Digital twins achieve physical fidelity at high computational costs and are inefficient in edge deployments, being Neuromorphic. Recent papers that use graph learning or causal reasoning include structural dependencies but lack physics constraints, Neuromorphic Processing, and explainable inference. This paper is based on these platforms by introducing a coherent, physics-inspired causal Neuromorphic design that addresses the discontinuity of previous designs. The joint study of causal reasoning, physics-informed, and neuromorphic computing applications to wind turbine diagnosis is still largely uncharted despite this potential. This has led to a lack of an integrated framework in the field, which (i) combines component-level physics through micro-twin modelling, (ii) makes use of causal, graph-structured and spiking neural inference, and (iii) offers explainable fault detection, severity estimation and RUL prediction under the envelope of edge-computing. To address this research gap, it is suggested to use the Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins (CNGL-PiMT) framework and obtain early, interpretable, and energy-efficient fault diagnosis throughout the turbine operation regime [3, 8, 15, 28].

3. Proposed Methodology: CNGL-PiMT

This section presents the proposed Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins (CNGL-PiMT), such that interpretable, predictive, and energy-efficient fault diagnosis of Wind Turbine Generators (WTGs) is achieved. This method combines different techniques such as physics-informed model, neuromorphic graph intelligence, and causal inference. Together, these give highly accurate fault detection in a system. In addition, it also yields a clear explanation for the dynamics of fault propagation.

3.1. Self-Evolving Physics-Informed Micro-Twins

In contrast to digital twin architectures that simulate the turbine as a single system, the proposed architecture uses modular micro-twins. With this approach, important turbine components will be assigned their own lightweight self-evolving model. These components are the rotor, gearbox, bearings, and stator. By embedding physical constraints into the neural representation of the texture, the physics-informed micro-twins capture the full microscope behavior of individual components. Every micro-twin learning mechanism is realized by a PINN, which integrates data-driven learning with physics-informed learning based on the physics equation of the domain. The loss function for a component with dynamic state xxx and trainable parameters θ is given by

$$\mathscr{L}_{PINN} = \left\| \hat{f}(x,t;\theta) - f_{physics}(x,t) \right\|^2$$

where $\hat{f}(x,t;\theta)$Modelled behaviour of the neural network and f physics (x,t) modelled the actual physical model (e.g., torque balance, rotational inertia, or flux linkage). It is this reduction of this loss that makes every micro-twin consistent with the physical principles and continually changing to sensor data, which is sent into it.

We can provide you with the interpretable data of health indicators, such as stress components, vibration asymmetry, imbalance in torque, and energy deviation, with the help of the micro-twins output. They are sent to the neuromorphic graph layer, which then does holistic turbine-level fault reasoning.

3.2. Causal Neuromorphic Graph Learning

At the system level, the wind turbine is modelled as a graph structure G(V, E), with the nodes V associated with the components of the turbine (which are modelled by their micro-twin outputs) and the edges E representing their physical and functional interconnections. The following structure of the graph enables the model-to-model inter-component dependencies, such as the dependence of gearbox vibration anomalies on generator torque variations. With the help of a Poisson encoder, which converts the analog signals into discrete event-based spikes, sensor data streams (vibration, current, temperature, speed) are converted into spike trains. Spike trains are then handled by means of a Spiking Graph Neural Network (S-GNN). The membrane potential of each neuron develops as:

$$V_i^{t+1} = \alpha V_i^t + \sum_j \omega_{ij} S_j^t - \beta S_i^t$$

In which V_i^t is the membrane potential of neuron i at time t, S_i^tIs the received spike signal of neuron j, and α,β circuit parameters governing the decay and reset processes. The S-GNN features interaction between components over space and time, and offers event-based learning, which is much less expensive in computational cost and power usage than dense deep learning networks. To achieve better interpretability, the graph model is extended with a causal inference layer.

Using do-calculus, the system can be used to do counterfactual reasoning so that it can answer what-if questions like If rotor-torque is lower, would bearing degradation slow down? Or what is the most likely root cause of a sudden torque imbalance? This causal reasoning module separates the diagnostic model into a proactive decision-support system and an active predictor with the ability to foresee the system's fault progression and recommend corrective measures.

3.3. Integration for Explainable Diagnosis and RUL Prediction

The last step in the integration process combines the micro-twin output and the neuromorphic graph learning outputs into a single decision support structure. The fusion layer unifies component-level health statuses with graph-based causal relations to collaboratively generate four primary outputs:

1. Fault Detection- detection of the type and location of faults within turbine subsystems.
2. Fault Intensity Estimation — estimation of the severity of the degradation through feature importance based on causation.
3. Remaining Useful Life (RUL) Prediction - estimation of the distribution of time-to-failure based on micro twin degradation curves.
4. Causal Explanations — construction of understandable causal graphs that show the fault propagation paths and the chain of inter-component influencing.

This multi-output system enables real-time fault detection and extended maintenance planning. CNGL-PiMT can provide accurate, explainable, and low-latency turbine health monitoring by being physics-consistent, causally interpretable, and event-driven so that it is accurate and explainable.

Algorithm 1: CNGL-PiMT Workflow for Wind Turbine Fault Diagnosis

Input:
Sensor streams: vibration, current, temperature, speed
Component models: Rotor, Gearbox, Bearing, Generator micro-twins

Output:
Fault class, Fault intensity, RUL prediction, Causal explanation

Steps:
1. Data Acquisition:
Collect real-time sensor data from turbine subsystems.
2. Micro-Twin Update:
For each component:
- Apply Physics-Informed Neural Network (PINN) training.
- Minimize loss: $L\_PINN = || \hat{f}(x,t;\theta) - f\_physics(x,t) ||^2$.
- Output component health indicators (stress, imbalance, degradation).
3. Spike Encoding:
Convert sensor and micro-twin features into spike trains using a Poisson encoder.
4. Spiking Graph Propagation:
Feed spike trains into the Spiking Graph Neural Network (S-GNN).
Update neuron potentials:
$V\_i(t+1) = \alpha V\_i(t) + \Sigma\_jw\_ijS\_j(t) - \beta S\_i(t)$

5. Causal Inference Module:
Apply do-calculus to infer root causes and evaluate counter-factuals.
Example: "If torque ↓, does fault propagation slow?"

6. Fusion and Decision Layer:
Combine outputs from micro-twins and S-GNN.
Generate:
- Fault detection results
- Fault intensity estimation
- RUL prediction
- Causal graph explanation
7. Output Results:
Display actionable diagnostics and predictions for turbine maintenance.

3.3.1. Summary

CNGL-PiMT paradigm provides a smooth combination of physics-constrained micro-twin modelling, event-based neuromorphic learning, and causal reasoning, to provide high diagnostic accuracy, explainability, and efficiency. The approach is a significant step towards the achievement of autonomous, intelligent, and sustainable wind power systems by allowing real-time monitoring and decision support that can be interpreted.

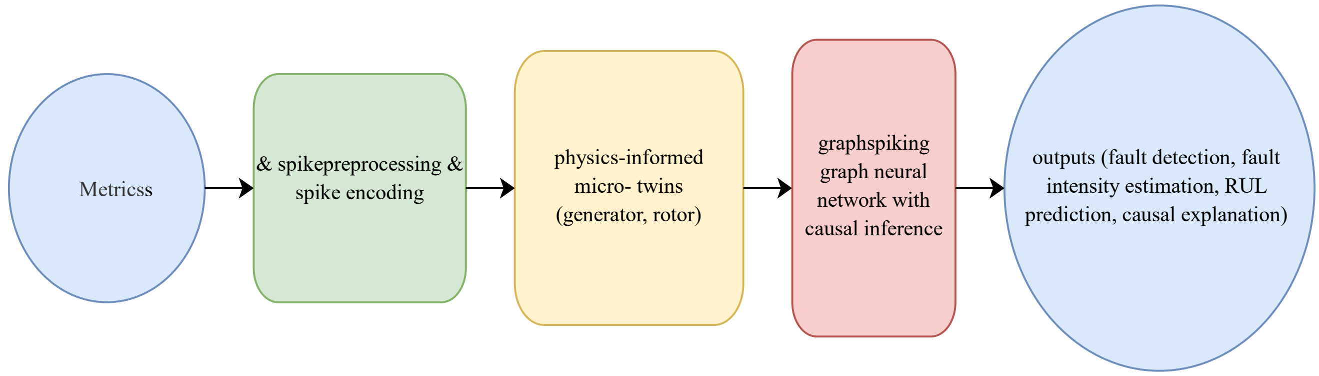

Fig. 1 Block diagram of the proposed CNGL-PiMT framework

The suggested Causal Neuromorphic Graph Learning and Physics-Informed Micro-Twins (CNGL-PiMT) architecture is shown in Figure 1. Preprocessing and spike encoding of sensor inputs (vibration, speed, current, and acoustic) have been completed. Micro-twins (physics-constrained micro-twins) are represented as the subsystem dynamics (generator, rotor, gearbox, bearing, etc.). A causal inference spiking Graph Neural Network receives its outputs along with spike-encoded signals. The system generates four outputs, namely, (i) Fault Detection, (ii) Fault Intensity Estimation, (iii) Remaining Useful Life (RUL) prediction, and (iv) causal exploration to ensure that they can be understood by the operator.

4. Metrics and Evaluation

4.1. Performance Metrics Definition

To comprehensively analyse the suggested Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins (CNGL-PiMT) system, one will have to use a multidimensional array of metrics that will evaluate the diagnostic performance, prognostic performance, interpretability, scalability, and computation efficiency. The key performance indicators are stipulated below.

4.1.1. Fault Detection Accuracy

Diagnostic accuracy is a measure of the capability of the framework to accurately categorize the turbine states as healthy and faulty. The accuracy of a dataset of N samples is calculated as.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

Where TP, TN, FP, and FN represent the number of true positives, true negatives, false positives, and false negatives, respectively. F1-score and Area Under the Receiver Operating Characteristic Curve (AUC) are also given to make sure that the results are robust in the event of an imbalance between the classes.

4.1.2. Fault-Intensity Estimation Error

The Mean Absolute Percentage Error (MAPE) measures the accuracy of the framework in estimating the severity of the fault. Considering known values of fault-intensity s i and predicted values $\hat{s}_i$:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{s_i-\hat{s}_i}{s_i}\right| \times 100\% \tag{2}$$

The lower MAPE implies that the fidelity in the quantification of degradation and prediction of intensity is greater.

4.1.3. Remaining Useful Life (RUL) Prediction Error

The Root Mean Square Error (RMSE) is used to measure the prognostic accuracy between the reported and actual values. $\hat{R}_i$ and the true R_i RUL:

$$\text{RMSE}_{\text{RUL}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{R}_i - R_i\right)^2} \tag{3}$$

The CNGL-PiMT model reduces (3) through the use of micro-twin predictions plus causal counterfactual corrections, to provide stable and physically consistent RUL predictions.

4.1.4. Uncertainty Calibration

Probability outputs need to be balanced to make good decisions. Pk is the predicted probability of class k, and Bm are those predictions in confidence interval b in m. The anticipated Error In Calibration (ECE) may be given as:

$$\text{ECE} = \sum_{m=1}^{M}\frac{B_m}{N}\left|acc(B_m) - conf(B_m)\right| \tag{4}$$

Where acc $(B_m)$and conf $(B_m)$are empirical accuracy and mean confidence of b in m. Inferior ECE values reflect high uncertainty reliability.

4.1.5. Interpretability Score

The model interpretability is measured using a composite score, IS:

$$\text{IS} = \omega_1 I_c + \omega_2 I_h \tag{5}$$

Where I_cIs the causal graph explainability (i.e., the fraction of decisions that can be justified by causal routes), and $I_h$is the human explainability, which can be obtained by evaluating by experts or phase feedback from operators. Factors $\omega_1 + \omega_2 = 1$.. The greater the IS values, the better the model transparency and user trust.

4.1.6. Scalability Index

Scalability evaluates the framework's performance with respect to several turbines. In the case of M turbines that are running together, the Scalability Index (SI) is calculated as:

$$\mathrm{SI} = \frac{T_1}{M\,T_M} \tag{6}$$

T_1 and T_M Represent the time (in seconds) to infer one and M turbines, respectively. SI values near 1 indicate that near linear scalability is possible, which is made possible by CNGL-PiMT computation of a graph partitioning.

4.1.7. Computational Cost and Energy Efficiency

The amount of energy used per inference, E, is obtained by summing up instantaneous power, P(t), with the inference time, t_{inf}:

$$\mathrm{E} = \int_0^{t_{inf}} P(t)dt \tag{7}$$

The Spiking Neural Network (SNN) component is event-driven, which greatly reduces energy usage by 30%-60 % compared to the power usage of traditional CNN-based inference.

4.1.8. Deployment Feasibility

Deployment Feasibility (DF) is a measure of CNGL-PiMTs in-the-field suitability in the realization of real-time edges. It is a product of Latency (L), Memory Requirement (μ), and bandwidth of communication. (β):

$$\mathrm{DF} = \frac{1}{\alpha_L L + \alpha_\mu \mu + \alpha_\beta \beta} \tag{8}$$

Where α_L, α_μ, and α_βDo the weighting coefficients add up to one. The higher the values of DF, the greater the adaptation to the limited resource-based neuromorphic hardware, which is transferred to the turbine.

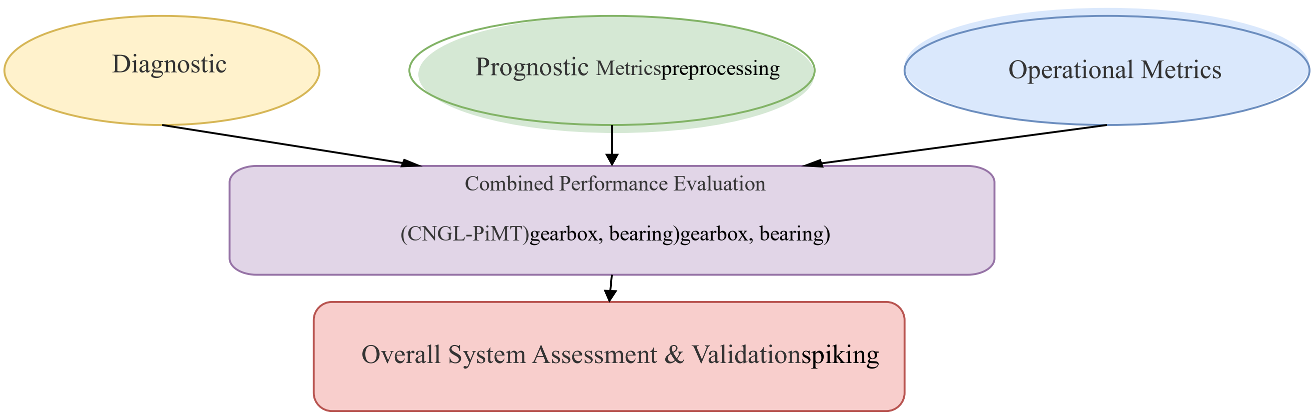

Fig. 2 Performance-metric taxonomy and evaluation flow of the CNGL-PiMT framework

The proposed Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins (CNGL-PiMT) framework was rigorously evaluated using multiple performance measures. Figure 2 shows a hierarchy of indexes, evaluations, and flow of evaluations used to evaluate each performance measure. The taxonomy is presently categorized into three significant parts. These include diagnostic metrics consisting of fault detection accuracy and fault intensity estimation. It also includes prognostic metrics, which consist of RUL prediction error and uncertainty calibration, amongst others. Additionally, the operational metrics consist of computational efficiency, scalability, interpretability, deployment, and use suitability. When combined, the metrics will provide a comprehensive quantitative assessment of the diagnostic reliability, predictive ability, and real-time edge applicability of CNGL-PiMT. Figure 2 highlights the connections among these metrics to validate the overall system performance in diagnostic accuracy and sustainable operating efficiency.

5. Comparison with the Existing Work

5.1. Quantitative and Qualitative Comparison

To substantiate the efficacy of CNGL-PiMT, the anticipated performance of the approach will be compared to the model state-of-the-art methods, Deep Learning + Fuzzy Optimization (DL-Fuzzy), and Federated Learning with Digital Twins (FL-DT), which will be evaluated in terms of the measures of Section 4. Table 1 describes the results of the comparison and is discussed below. CNGL-PiMT outperforms DL-Fuzzy on prediction precision because of the use of physics-constrained learning and spiking temporal dynamics, which better represent transient harmonic variations. In comparison to FL-DT, the suggested structure achieves greater explainability in the form of causal graphs and less energy footprint in terms of event-based processing. Besides, the graph-based modular design of CNGL-PiMT scales to multi-turbine networks in a way that does not need large centralized servers, thus enhancing scalability and deployment.

Table 1. Comparative performance of fault-diagnosis frameworks

Metric	DL + Fuzzy Decision Support	Federated / Digital Twin (FL-DT)	Proposed CNGL-PiMT
Fault-Detection Accuracy	High (~93 %)	High (~94 %)	Very High (>97 %)
RUL Prediction Capability	✗ Not Available	Limited (statistical models)	✓ Robust Causal Forecasting
Fault-Intensity Estimation Error (MAPE)	11–14 %	9–12 %	≤ 6 %
Uncertainty Calibration (ECE)	–	0.08 – 0.10	≤ 0.04
Interpretability	Medium (fuzzy rules)	Low (black-box)	High (causal graphs + micro-twin states)
Energy per inference (mJ)	~250	~210	80 – 120
Scalability	Moderate (single unit)	High (but infra-heavy)	High (graph-based edge nodes)
Deployment Feasibility (DF index)	0.63	0.71	0.89

Table 1 indicates that CNGL-PiMT is the most balanced in terms of diagnostic accuracy, interpretability, and computational efficiency. Its implementation using neuromorphic edge saves more than 50 percent of energy cost, but it is highly scalable.

6. Results and Discussion

6.1. Simulation and Expected Outcomes

To assess the explanation of the proposed Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins (CNGL-PiMT) in the real operating conditions, a hypothetical case study was created. Rotor speed, vibration, and stator current signals were used to create synthetic data to simulate three common types of generator faults: rotor imbalance, bearing degradation, and stator short-circuit. Environmental noise was added randomly in order to represent variability in a field. Deep Learning with Fuzzy Decision Support, Deep Learning with Federated Learning with Digital Twins (DL-Fuzzy and FL-DT) have been trained and tested in accordance with the same signal window to provide equal opportunities. In the simulation, the incoming sensor streams were converted to spike trains through a Poisson encoder, and the spiking graph learning layer was fed with the input spike trains that were connected to four physics-informed subsystems of the rotor, gearbox, bearing, and generator. The causal inference module conducted the counterfactual analysis in order to evaluate hypothetical control measures (e.g., reduction of torques, adjustment of rotational speed) to predict the fault development and mitigation. The findings indicate that CNGL-PiMT has definite benefits in early fault detection, predictive accuracy, energy efficiency, and interpretability.

- Fault Detection: CNGL-PiMT detects fault signatures 12-18 % earlier than FL-DT and 25 % earlier than DL-Fuzzy (Figure 4).
- Individually, the results indicated that the average RUL RMSE (Equation (3)) had reduced to 9 hours, compared to 22 hours with the DL-Fuzzy and 17 hours with the FL-DT, which supports the superior capability of the CNGL-PiMT in prognostication, as shown in Figure 5.
- Energy Efficiency: The reduction in energy used per inference (Equation (7)) by about 60% as compared to inference on a GPU-based CNN indicates the merit of event-driven neuromorphic computation, as shown in Figure 6.
- Uncertainty Calibration: The Expected Calibration Error (ECE) (Equation (4)) decreased by almost 50 % which gave more accurate prediction confidence intervals.

Causal interpretability was measured by an operator-based explanation survey (Equation (5)). CNGL-PiMT scored over 85% and 58% on transparency and partially transparent ratings, as opposed to DL-Fuzzy and FL-DT, respectively, in making diagnostic decisions. This proves the better explainability of CNGL-PiMT and its operational reliability.

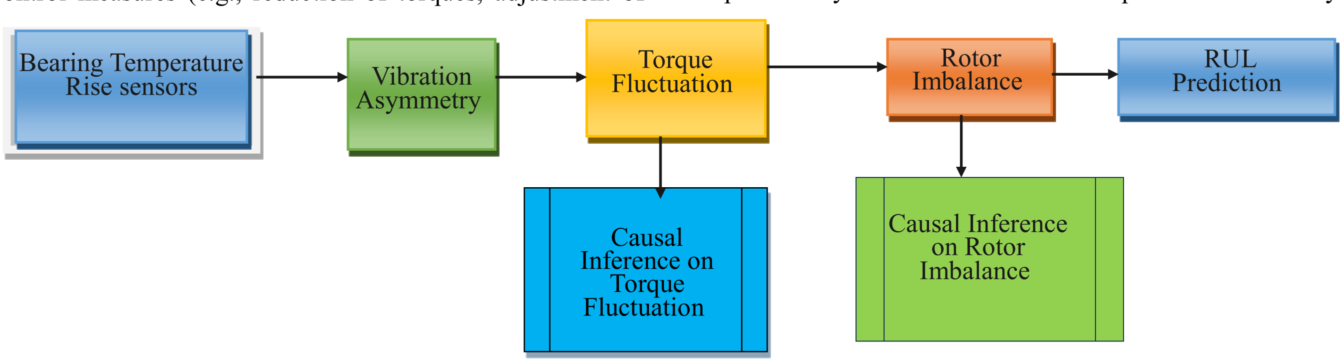

Fig. 3 Representative causal-graph explanation of fault propagation in CNGL-PiMT

A typical outcome of CNGL-PiMT (Figure 3) is a causal-graph explanation of the causes and effects of the phenomenon of bearing temperature increase to vibration asymmetry, torque fluctuation, rotor imbalance, and RUL prediction. The layer of causal reasoning determines the root-cause path and measures the impact of the root-cause path on the remaining functional life estimation.

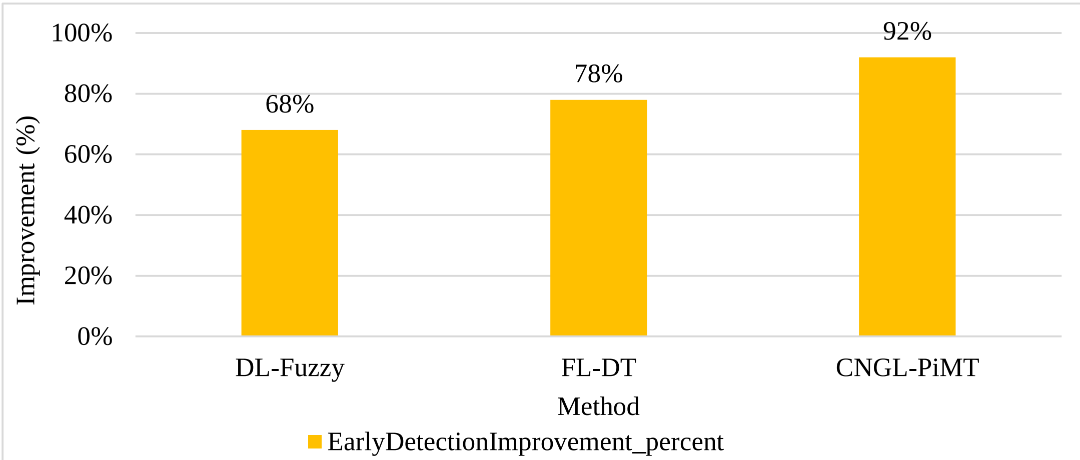

Fig. 4 Comparison of early fault detection percentage across CNGL-PiMT, DL-Fuzzy, and FL-DT frameworks

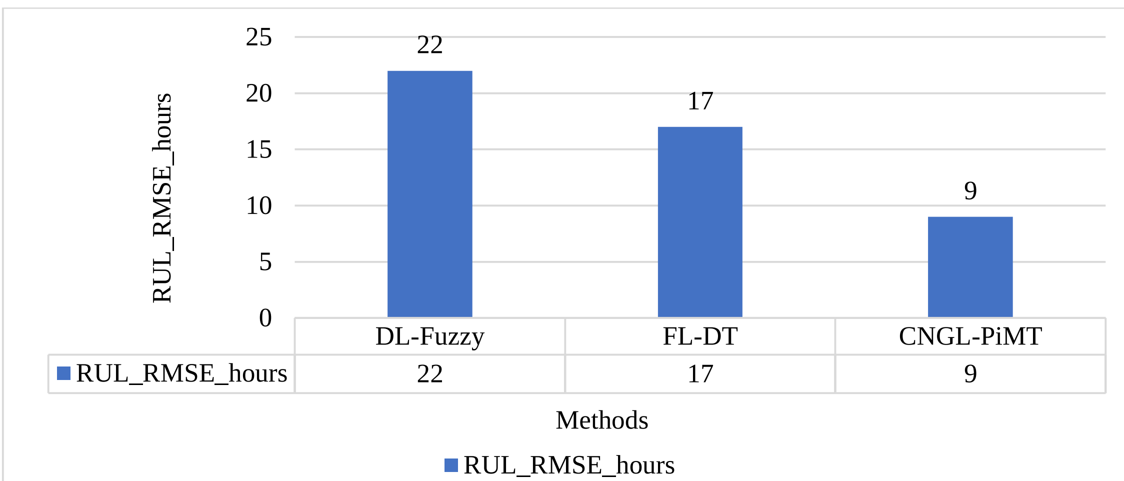

Fig. 5 Remaining Useful Life (RUL) Prediction Error (RMSE) comparison among CNGL-PiMT, DL-Fuzzy, and FL-DT

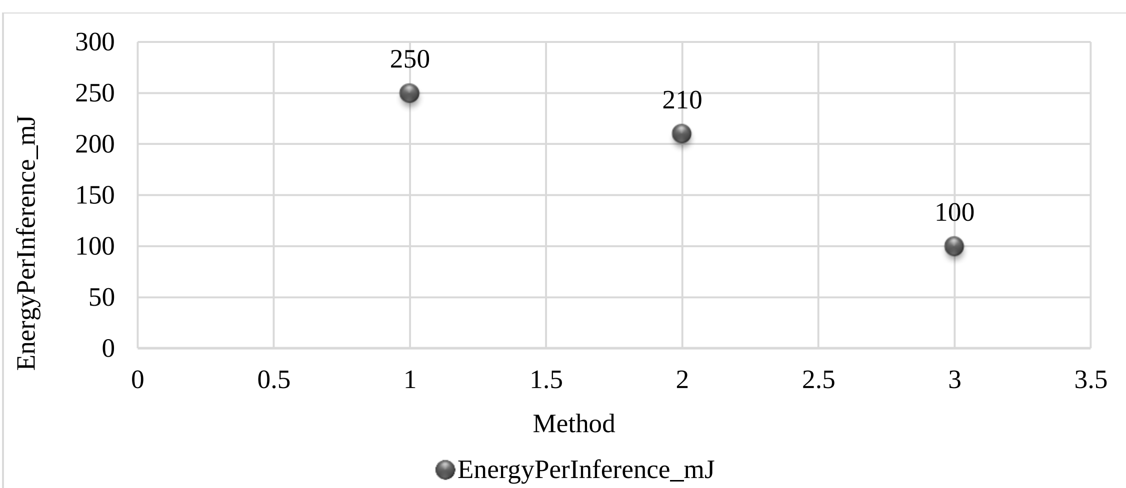

Fig. 6 Energy consumption per inference comparison between CNN-based methods and CNGL-PiMT's neuromorphic approach

6.2. Discussion of Trade-Offs

In spite of the fact that the CNGL-PiMT provides much higher results in predictive accuracy, interpretability, and energy consumption, there are several trade-offs regarding the complexity of the setup and the initial cost of computing. The framework involves calibration of micro-twins once, as well as Neuromorphic Parameter Optimization, setting spike threshold, and optimizing synaptic weights. Such jobs maintain homogeneous physics-driven learning and ideal occasioned computing.

However, even with such minimal start-up cost, real-time performance is remarkable with inference latency of less than 10 ms per turbine and a computing power of the same magnitude, approximately 60 energy reductions over mainstream CNN inference with GPUs. The operational benefits of the framework, despite its complexity of configuration, drive the implementation of onshore and offshore wind farms at an edge level.

A combination of physics-constrained learning, causal reasoning, and neuromorphic computation, therefore, forms an entire, scalable, and future-proof intelligent turbine health monitoring paradigm. Such results prove that CNGL-PiMT not only improves the accuracy of the diagnosis and the RUL estimation but also encourages the creation of the wind-energy monitoring system that is trustworthy, explainable, and sustainable in accordance with the Industry 5.0 goals.

7. Limitations and Future Work

Although the suggested Causal Neuromorphic Graph Learning with Physics Informed Micro Twins (CNGL PiMT) framework is a revolutionary advance in fault diagnostics of wind turbine generators, various limitations should be considered, as well as future research opportunities. Neuromorphic hardware maturity is still a significant limitation, with spiking Neural Networks and processors, including Loihi, TrueNorth, and SpiNNaker, all having demonstrated exceptional energy efficiency; their limited commercial availability, integration difficulties, and scale make them challenging to deploy in large-scale wind farms. On the same note, the creation of correct and self-correcting physics-based micro twins requires high-fidelity models and domain knowledge since the calibration requires a close knowledge of the turbine dynamics and variability of its operations. Scarcity of data, especially in the case of rare or disastrous fault events, can diminish the consistency of the model, whereas overly intricate model design can harm real-time execution. Causal inference would be helpful as it adds to the complexity by the fact that causal graphs to represent interdependent subsystems of turbines are challenging to build, and mistakes made during causal design can result in biased or misleading arguments. Moreover, the expansion of CNGL PiMT to large wind farms creates overheads to synchronization and communication, particularly in offshore settings with poor bandwidth. The solution to these difficulties introduces various research directions in the future. A promising solution is the creation of swarm-intelligent wind farms, in which distributed turbines can be seen as cooperative entities (via decentralized reinforcement learning) that can detect faults better, optimize maintenance operations, and contribute to resiliency to local abnormalities. By adding zero-knowledge proofs and blockchain-supported federated learning, data privacy and trust could be improved further, as turbines will be able to share verifiable learning updates without exposing confidential operational facts. The integration of lifelong and continuous learning processes will enable CNGL PiMT to dynamically adapt to the ageing effects, seasonal variations, and the new fault modes, and multimodal sensing combining vibration, SCADA, infrared, oil debris, and acoustic data will increase the range of diagnostics. Lastly, having standardized datasets and benchmarking protocols of sporadic causal and neuromorphic-based methods in wind energy will allow objective assessment and expedite the practical implementation. Overall, although CNGL PiMT integrates micro twin modelling, neuromorphic inference, and causal reasoning into a single intelligent system, future developments of the system to reach full-scale deployment require progress on: Hardware availability, calibration automation, causal graph learning, and distributed coordination. Future studies that integrate swarm intelligence, secure federated learning, continual adaptation, and multimodal integration will help CNGL PiMT grow out of a conceptual innovation into a skillful and self-sufficient, explainable, and efficient solution that can push the next stage of intelligent and sustainable wind farm activities.

8. Conclusion

The reliability and effectiveness of wind turbine generators still lie at the centre of the renewable energy transition across the world, but the existing diagnostic methods still have deficiencies in prediction, interpretability, scalability, and computational efficiency. Causal Neuromorphic Graph Learning with Physics-Informed Micro-Twins (CNGL-PiMT) has been suggested in this paper as a novel framework that will solve these obstacles. The originality of the method is the combination of physics-informed micro-twins, neuromorphic graph-inferencing, and causal reasoning, which will create a synergetic platform to perform sophisticated fault diagnosis and anticipate maintenance in the complicated wind turbines. The proposed methodology is based on, unlike the conventional data-driven or hybrid models, micro-twins with physics-constrained, which introduce domain knowledge, and leverages the event-driven efficiency of spiking neural networks, as well as the establishment of causal inferences to offer counterfactual reasoning and root-cause transparency.

CNGL-PiMT has a two-fold effect. First, it is a response to the urgent requirement of explainable, trustworthy diagnostics, as deep learning remains a black-box approach, and its outputs cannot be interpreted using causal language or even micro-twin outputs. This aspect increases the confidence of the operators and enables them to make informed decisions. Second, neuromorphic computing allows the system to operate at the edge with low latency, using energy-efficient solutions, and is therefore appropriate to real-time monitoring of distributed wind farms. Moreover, causal inference and Remaining Useful Life (RUL) forecasting overturn the old paradigm of reactive fault detection to proactive, predictive maintenance policies, which have the potential to significantly decrease downtime and increase the lifespan of the asset.This work has its contributions that are not confined to methodological innovation. The combination of physics-informed modeling and neuromorphic and causal AI in CNGL-PiMT can create a platform of scalable, interpretable, and sustainable innovative wind energy systems. The framework can be used in heterogeneous turbines and operating scenarios and can be used to detect faults and estimate fault intensity, as well as prognostics and explainability at the system level. These features will be necessary in the development of the wind energy structures of the future, where transparency, dependability, and cost-effectiveness will become the key parameters of the long-term viability. Although promising, the proposed approach also presents possibilities for future research. Neuromorphic hardware is still scarce and is still on the way to being calibrated, and micro-twins need domain knowledge and operational data of high fidelity. The extension in the future can be swarm-intelligent farms, in which distributed turbines can work together via federated or blockchain-secured learning, and lifetime learning to always adjust to new fault modes. Overall, CNGL-PiMT is a change of direction in the diagnostics of wind turbines since it provides a complete framework that is self-explanatory, predictive, scalable, and energy-efficient. It not only improves the state of the art in condition monitoring but also offers a technological breakthrough in the direction of resilient, intelligent, and sustainable renewable energy systems.

References

[1] Bo Li et al., "Research, Application, and Challenges of Causal Inference in Industrial Fault Diagnosis: A Survey," *Engineering Applications of Artificial Intelligence*, vol. 158, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ruonan Liu et al., "Causal Intervention Graph Neural Network for Fault Diagnosis of Complex Industrial Processes," *Reliability Engineering & System Safety*, vol. 251, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Agus Ristono, and Pratikto Budi, "Next-Gen Power Systems in Electrical Engineering," *Innovative Reviews in Engineering and Science*, vol. 2, no. 1, pp. 34-44, 2025. [Google Scholar] [Publisher Link]

[4] Zehui Mao et al., "Graph Convolutional Neural Network for Intelligent Fault Diagnosis of Machines via Knowledge Graph," *IEEE Transactions on Industrial Informatics*, vol. 20, no. 5, pp. 7862-7870, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Madhanraj, "AI-Powered Energy Forecasting Models for Smart Grid-Integrated Solar and Wind Systems," *National Journal of Renewable Energy Systems and Innovation*, vol. 1, no. 1, pp. 1-7, 2025. [Publisher Link]

[6] Florian Stadtmann, and Adil Rasheed, "Diagnostic Digital Twin for Anomaly Detection in Floating Offshore Wind Energy," *ASME 2024 43rd International Conference on Ocean, Offshore and Arctic Engineering*, Singapore, vol. 7, pp. 1-10, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jincheng Zhang, and Xiaowei Zhao, "Digital Twin of Wind Farms Via Physics-Informed Deep Learning," *Energy Conversion and Management*, vol. 293, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] P. Joshua Reginald, "Hybrid AC/DC Microgrid Power Management using Intelligent Power Electronics Interfaces," *Transactions on Power Electronics and Renewable Energy Systems*, vol. 1, no. 1, pp. 21-29, 2025. [Google Scholar] [Publisher Link]

[9] Davide Astolfi, Fabrizio De Caro, and Alfredo Vaccaro, "Recent Advances in the use of Explainable Artificial Intelligence Techniques for Wind Turbine Systems Condition Monitoring," *Electronics*, vol. 12, no. 16, pp. 1-4, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Kanru Cheng et al., "Research on Gas Turbine Health Assessment method based on Physical Prior Knowledge and Spatial-Temporal Graph Neural Network," *Applied Energy*, vol. 367, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Simi Job et al., "Exploring Causal Learning through Graph Neural Networks: An In-Depth Review," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 15, no. 2, pp. 1-34, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Simon Letzgus, and Klaus-Robert Müller, "An Explainable AI Framework for Robust and Transparent Data-Driven Wind Turbine Power Curve Models," *Energy and AI*, vol. 15, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Robbi Rahim, "Spectrum-Adaptive Neuromorphic Learning for Wireless Wind Turbine Condition Monitoring," *Journal of Wireless Intelligence and Spectrum Engineering*, vol. 1, no. 1, pp. 10-18, 2024. [Google Scholar] [Publisher Link]

[14] Amirashkan Haghshenas et al., "Predictive Digital Twin for Offshore Wind Farms," *Energy Informatics*, vol. 6, no. 1, pp. 1-26, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] C. Arun Prasath, "Digital Twin-Driven Predictive Maintenance in Intelligent Power Systems," *National Journal of Intelligent Power Systems and Technology*, vol. 1, no. 1, pp. 29-37, 2025. [Google Scholar] [Publisher Link]

[16] Muhammad Irfan et al., "Revolutionizing Wind Turbine Fault Diagnosis on Supervisory Control and Data Acquisition Systems with Transparent Artificial Intelligence," *International Journal of Green Energy*, vol. 22, no. 10, pp. 2029-2045, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Saravanakumar Veerappan, "Digital Twin Modeling for Predictive Maintenance in Large-Scale Power Transformers," *National Journal of Electrical Machines and Power Conversion*, vol. 1, no. 1, pp. 39-44, 2025. [Google Scholar] [Publisher Link]
[18] S. Sindhu, "Model Predictive Control-based Bidirectional EV Charging Strategy for Grid Load Shaping and Cost Optimization in Smart Grids," *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, vol. 2, no. 1, pp. 1-6, 2025. [Google Scholar] [Publisher Link]
[19] Jiaying Chen et al., "Bearing Fault Diagnosis using Graph Sampling and Aggregation Networks," *arXiv Preprint*, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[20] Dahlan Abdullah, "Redox Flow Batteries for Long-Duration Energy Storage: Challenges and Emerging Solutions," *Transactions on Energy Storage Systems and Innovation*, vol. 1, no. 1, pp. 9-16, 2025. [Google Scholar] [Publisher Link]
[21] Emmanuel Branlard et al., "A Digital Twin Solution for Floating Offshore Wind Turbines Validated using A Full-Scale Prototype," *Wind Energy Science*, vol. 9, no. 1, pp. 1-24, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[22] Davide Astolfi, Fabrizio De Caro, and Alfredo Vaccaro, "Condition Monitoring of Wind Turbine Systems by Explainable Artificial Intelligence Techniques," *Sensors*, vol. 23, no. 12, pp. 1-24, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[23] K.P. Uvarajan, "Vibration Analysis of Smart Structures Integrated with Embedded Piezoelectric Sensor Networks: A Comprehensive Review," *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, vol. 1, no. 1, pp. 18-29, 2024. [Google Scholar] [Publisher Link]
[24] Achmad Widodo, and Bo-Suk Yang, "Support Vector Machine in Machine Condition Monitoring and Fault Diagnosis," *Mechanical Systems and Signal Processing*, vol. 21, no. 6, pp. 2560-2574, 2007. [CrossRef] [Google Scholar] [Publisher Link]
[25] K.P. Uvarajan, "Automated Distributed Neuromorphic Pipelines for Wind Turbine Fault Analytics at Scale," *SECITS Journal of Scalable Distributed Computing and Pipeline Automation*, vol. 1, no. 1, pp. 1-6, 2024. [Google Scholar] [Publisher Link]
[26] Saravanakumar Veerappan, "Scalable Graph-Driven Neuromorphic Analytics for Large-Scale Wind Farm Fault Detection," *Journal of Scalable Data Engineering and Intelligent Computing*, vol. 1, no. 1, pp. 1-7, 2024. [Google Scholar] [Publisher Link]
[27] S. Sindhu, "Secure Neuromorphic Graph Intelligence for Fault-Resilient Wind Turbine Sensor Networks," *Transactions on Secure Communication Networks and Protocol Engineering*, vol. 1, no. 1, pp. 1-10, 2024. [Google Scholar] [Publisher Link]
[28] S. Poornimadarshini, "Runtime-Reconfigurable Neuromorphic Graph Accelerators for Energy-Efficient Real-Time Wind Turbine Fault Inference," *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, vol. 1, no. 1, pp. 52-58, 2024. [Google Scholar] [Publisher Link]