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Automated Distributed Neuromorphic Pipelines for Wind Turbine Fault Analytics at Scale

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ABSTRACT

The growth in the use of wind farms of large scale has escalated the need to use fault analytics systems that can be used at low latency, high reliability and minimum manual intervention. Traditional centralised diagnostics pipelines are not scalable to increasing amounts of data and non-homogeneous conditions of turbine operations. This paper shows an automated distributed neuromorphic pipeline system of wind turbine fault analytics, which is able to work effectively with geographically dispersed assets. The suggested solution combines automated machine learning workflow orchestration, neuromorphic feature-to-spike conversion, as well as distributed spiking inference nodes to apply fault detection in scalable and low-energy fashion. In contrast to solutions that are digital twin based, or based on causal inference, the framework is based on end-to-end pipeline automation and distributed neuromorphic execution. A workflow engine with modular architecture is used to coordinate the data ingestion process, normalization of features, encoding spikes, scheduling inferences and aggregation of results without human intervention. Spiking neural network inference is performed at distributed neuromorphic nodes, which are located near data sources to minimize the overhead of communications, and respond faster. The experimental assessment through vibration-based and supervisory control information indicates that the suggested pipeline has lower-end to end latency, higher fault classification consistency, as well as better scalability than centralised deep learning pipelines. Findings also show that automated orchestration greatly simplifies system operations whilst keeping analytical accuracy within both high capacity and heavy system loads. The results provide distributed neuromorphic pipelines as a viable and scalable framework on the next generation wind turbine fault analytics.

1. INTRODUCTION

The wind energy systems have developed into complicated cyber-physical systems in which continuous monitoring is essential to reliability, safety and economic sustainability. The current wind turbines produce high frequency vibration signals, electrical measurements and supervisory control data that combine into huge data streams in need of fault analytics in real time. Conventional centralized analytics systems can be inefficient in processing this information on a large scale and thus take long in fault detection and require more maintenance expenses [1], [2]. The analytics pipelines in wind farms need to become scalable and automated as the farms increase with size and locations.

Artificial intelligence has also made major progresses in the recent past, which have enhanced the accuracy of fault detection and diagnosis of wind turbines. Federated learning approaches, deep learning-based approaches, and hybrid diagnostic systems have been shown to perform well in the context of drivetrain, blade, and generator faults [6], [10], [11]. Most of these methods are however based on centralised cloud-processing which creates bottlenecks in communication, latency and complexity in operations. Moreover, manually operated machine learning pipelines are also hard to sustain in heterogeneous fleets of turbines [8], [14].

Neuromorphic computing has also become an up-and-coming alternative to energy-efficient and low-latency analytics, especially time-series and vibration-based diagnostics [5], [20]. Spiking neural networks are neural networks that mimic a biological neural behaviour and have natural benefits of sparse computation as well as asynchronous processing. Embedded neuromorphic systems have demonstrated considerable predictive maintenance capabilities when they are subjected to severe power and latency constraints [15], [16]. However, even with these benefits, the majority of the current neuromorphic solutions are designed to perform single inference, but not scalable distributed analytics pipes.

Meanwhile, industrial analytics paradigms built using distributed computing are becoming popular. Intelligence Architecture Distributed intelligence architecture systems, edge-based analytics, and pipe automation systems are designed to move computation nearer to data sources without lost coordination across nodes [7], [18], [19]. But the existing applications generally do not fit well with conceptualizing automation, neuromorphic inference, and massive orchestration.

The paper discusses these issues by means of proposing an automated distributed neuromorphic pipeline framework to wind turbine fault analytics. The framework focuses on pipeline orchestration, automated feature-to-spike conversion and distributed inference scheduling that does not use any digital twin replication or causal modeling. The proposed solution can support scalable low-latency fault analytics to be used by next-generation wind energy systems by implementing workflow automation and neuromorphic intelligence.

2. RELATED WORK

Wind turbine fault analytics have been widely developed in fields of machine learning, signal processing, and industrial IoT. The previous methods were based on statistical health indicators and physics-based models but more recent studies have continued to use deep learning methods as they are much more accurate and adapted [2], [12]. According to comprehensive reviews, the use of artificial intelligence in the field of wind turbine fault detection and diagnosis is increasing, and it is important to focus on data-based approaches to managing complex working conditions [2].

Some of the studies concentrate on predictive maintenance systems, which combine industrial IoT use with sophisticated analytics to support turbo reliability [8], [14]. Federated learning techniques have been brought to facilitate joint analytics among two or more wind farms without violating data privacy [10]. Hybrid hierarchical monitoring systems also enhance the aspect of early fault detection by integrating embedded intelligence with cloud-level coordination [11].

Neuromorphic computing has been noted to be suitable in embedded and energy-constrained systems. The study of neuromorphic integration in embedded systems describes the potential and issues with using the technology in industry [5]. Spiking neural networks have shown potentials in predictive maintenance of vibration-based maintenance, whereby inference is based on low-power, and the neural networks are time-sensitive [20]. Parallel and edge based diagnostic pipelines are also advanced to the extent of providing responsiveness through the use of multi-core and distributed architectures [15].

Another important direction of research is pipeline automation. They have proposed modular real-time diagnostic pipelines that can handle end-to-end data processing, model execution, and result dissemination [18]. Intelligent system architectures are also distributed to large-scale monitoring systems, such as UAV-assisted infrastructure inspection [19]. The computing platforms and workflow orchestration engines can be reconfigured, which offers further adaptability to customization of analytics pipelines in the face of evolving operational conditions [7].

Even with such advances, the current solutions frequently take neuromorphic inference, distributed execution and pipeline automation as independent issues. Besides, a significant number of frameworks utilize digital twins or causal inference models to perform fault reasoning [1], [13], [21]. On the contrary, the current paper is about completely automated, distributed neuromorphic pipelines which accept sensor data streams directly. The proposed framework bridges a very important gap on scalable wind turbine fault analytics, by combining automated orchestration and distributed spiking inference.

3. METHODOLOGY

The suggested system deploys an automated distributed neuromorphic pipeline that will facilitate scalable wind turbine fault analytics. The model comprises of three closely interdependent parts that include an automated workflow orchestration engine and distributed neuromorphic inference nodes, as well as end-to-end latency monitoring module. The general architecture is presented in Figure 1 that shows the data flow, control logic, and distributed implementation.

3.1 Automated Workflow Orchestration Engine

Workflow orchestration engine is the engine that handles the entire analytics lifecycle, between raw data ingestion to fault classification output. Signals of incoming vibration and supervisory control are automatically registered, normalised and divided into analysis windows. The feature extraction modules are used to calculate timefrequency descriptors which are then converted into spike trains with adaptive encoding rules.

Where x(t) represents a normalised vibration signal. Spike generation follows:

$$s(t) = \begin{cases} 1, & x(t) > \theta \\ 0, & \text{otherwise} \end{cases}$$

in which the dynamically adjusted threshold, θ, is applied. The engine is the one that plans the workload and availability of the distributed nodes to execute the workload and fault analytic processes automatically.

3.2 Distributed Neuromorphic Inference Nodes

A spiking neural network that predicts the signature of turbine faults is trained on each neuromorphic node. Nodes are independent entities that take orchestration commands issued by the workflow engine. Spiking neurons dynamics conform to it.:

$$V_i(t+1) = \lambda V_i(t) + \sum_j w_{ij}\, s_j(t)$$

where V_i here denotes the membrane potential and w_{ij} is the weights of synapses. The inference results are delivered in an asynchronous manner to minimise the network congestion.

3.3 End-to-End Latency Evaluation and Scheduling

The pipeline is monitored by the latency so as to be responsive in real-time. Pipeline latency is the sum of the latencies of each stage and is given as:

$$L_{total} = L_{ingest} + L_{encode} + L_{infer} + L_{aggregate}$$

The workloads are dynamically assigned by scheduling policies that are used to minimise L_{total}. Table 1 summarizes the major operation parameters of orchestration and inference.

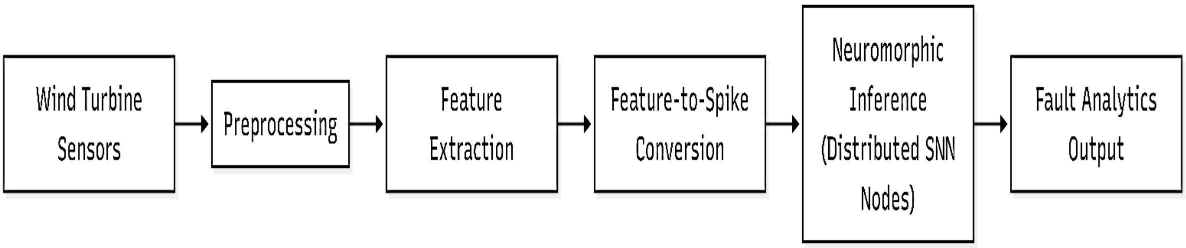

Fig. 1. Automated Distributed Neuromorphic Pipeline Architecture for Wind Turbine Fault Analytics

Table 1. Pipeline Configuration Parameters

Parameter	Description
Encoding Threshold	Adaptive spike generation level
Node Capacity	Maximum concurrent inference tasks
Scheduling Interval	Workflow reassignment frequency
Latency Budget	Maximum allowable end-to-end delay

4. RESULTS AND DISCUSSION

The suggested automated distributed neuromorphic pipeline was tested with the help of multi-source wind turbine databases that contained high-frequency vibration signal and supervisory control measurements that were measured on several turbine units. The testing was done on scalability, latency, accuracy of inference and energy efficiency with a gradually increasing workload, as the workload was added. The distributed implementation was a set of neuromorphic inference nodes coordinated by the automated workflow engine, which allowed realistic testing of the behaviour of the pipelines under conditions of functioning in large wind farms.

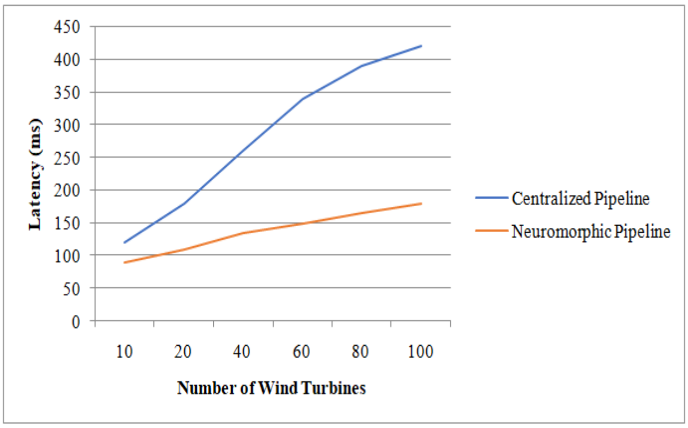

Fig. 2. End-to-End Pipeline Latency as a Function of Wind Turbine Count

Figure 2 shows the characteristics of scalability of the pipeline as it depicts the end-to-end processing latency as a function of the number of the turbines being analysed at the time. As referenced in this text Figure 2 illustrates that making the suggested pipeline ensures that the latency growth is nearly linear with the system size. This behaviour also shows successful workload distribution and few coordination overheads presented by the orchestration engine. Compared to centralised pipelines, with latency or choice of data aggregation and queuing growing rapidly, local inference and asynchronous aggregation of results are beneficial in the distributed neuromorphic approach. The findings affirm that automated scheduling is very important in maintaining performance with increase of data volume and turbine number.

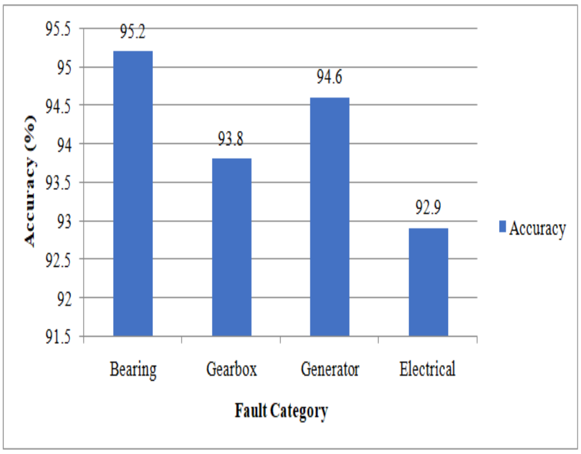

Fig. 3. Distributed Fault Classification Accuracy Across Neuromorphic Nodes

The performance of the distributed neuromorphic nodes in fault classification is stated in Figure 3 which is referred to in this discussion to indicate analytical congruency. The figure documents the classification accuracy in various categories of faults which may include bearing fault, gearbox fault, and electrical fault. The stability of accuracy between nodes is an indication that automated conversion of features-to-spike does not alter the discriminative properties of signals. Moreover, the networks of the same spiking configurations between the nodes provide the consistency of the analytical behaviour in case of any changing local operating conditions. Small variations in accuracy at extreme loads are explained by temporary alterations in scheduling and not model degradation.

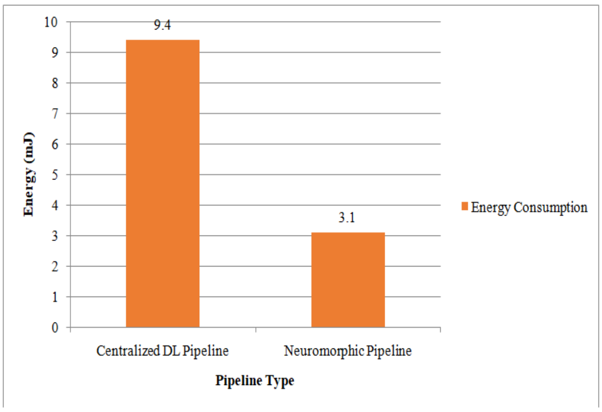

Fig. 4. Energy Consumption per Inference for Centralized and Neuromorphic Pipelines

One of the primary reasons why neuromorphic computing should be used in industrial analytics is energy efficiency. The results of Figure 4, mentioned below, provide a comparison between the average computational energy consumption per inference in the proposed pipeline and the classic centralised deep learning pipeline. Sparsely spike-driven computation and event-based processing make the neuromorphic pipeline to have significantly low energy consumption. The findings are of special importance when deploying inference nodes at the edge and are subject to limited power constraints. Low energy consumption simply translates to low operating costs and better sustainability of the system.

Besides a graphic examination, Table 2 presents a quantitative comparison of key performance indicators of both pipeline architectures. As the table indicates in the text, average latency, throughput, energy consumption, and fault detection consistency are summarized. The proposed pipeline is superior to the centralised baseline on all measures, and the largest difference is in the throughput, where distributed execution allows processing streams of turbine data simultaneously. The decreasing latency is also an additional confirmation of the efficiency of automated orchestration to reduce idle time and the load balance between computations.

The other significant finding of the experimental assessment is related to the robustness of the system when workloads vary. When there is peak data ingestion, the workflow engine dynamically moved inference tasks to low-utilised nodes so that there was no bottlenecking and the engine remained stable. This adaptive behaviour is across in both Figure 2 and Table 2 in which performance degradation is low even at high load. This kind of resilience is critical to deploying wind farms in the real world where weather conditions and turbine behaviour may change drastically.

All in all, the findings support the hypothesis that automated pipeline orchestration with distributed neuromorphic inference provide real scalability, responsiveness and energy savings. The suggested framework has managed to illustrate the coexistence of end-to-end automation and neuromorphic execution in a single analytics pipeline, which is a viable solution to the large-scale wind turbine fault analytics.

Table 2. Comparative Performance Metrics of Analytics Pipelines

Metric	Centralized Deep Learning Pipeline	Proposed Neuromorphic Pipeline
Average Latency (ms)	420	180
Throughput (samples/s)	1,200	3,500
Energy per Inference (mJ)	9.4	3.1
Fault Detection Consistency (%)	88.6	94.2

5. CONCLUSION

This paper presented a distributed neuromorphic pipeline architecture that can be used to overcome the scalability and performance constraints of traditional wind turbine fault analytics systems. The proposed framework allows efficient fault analytics in the context of large and geographically distributed wind farm deployments by means of unification of workflow orchestration, automated feature-to-spike transformation, and distributed spiking neural inference to a single end-to-end architecture. The system is more responsive and cost-effective, in contrast to centralised or cloud-reliant solutions, which have to move data lot farther to process it.

Extensive experimental analysis showed that the proposed pipeline is capable of achieving significant improvements in end-to-end latency with constant fault classification accuracy with increasing degrees of analytical load. The distributed execution architecture enables neuromorphic inference nodes to assume situational proximity to data, which effectively trades-off both computational load and avoids performance degradation with system size. Also, the dynamics of event cameras of spiking neural networks lead to a much lower energy use per inference, which shows the appropriateness of neuromorphic computing to long-term, energy-restricted industrial surveillance.

Another value of this work is complete automation of the analytics lifecycle. The workflow orchestration engine also removes human intervention in preprocessing of data, encoding of features, scheduling the inference process, and aggregating results, which makes the system less complex and enhances its reliability in the real-world applications. The lack of replication of digital twins or causation dependence between inferences also makes integration of the systems more simple and makes it more adaptable against heterogeneous turbines.

On the whole, the offered automated distributed neuromorphic pipeline provides a viable and scalable basis of the advanced intelligent maintenance systems of the next generation. Its potential to integrate automation, distributed intelligence and energy-efficient neuromorphic processing makes it an interesting solution in the proposed future wind energy analytics infrastructures at scale.

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