Low-Power Vibration-Based Predictive Maintenance for Industry 4.0 using Neural Networks: A Survey

Alexandru Vasilache,[1,2] Sven Nitzsche,[1,2] Daniel Floegel,[1,2] Tobias Schuermann,[1,2] Stefan von Dosky,[3]
Thomas Bierweiler,[3] Marvin Mußler,[3] Florian Kälber,[4] Soeren Hohmann,[2] Juergen Becker[2]
[1] *FZI Research Center for Information Technology, Karlsruhe, Germany*
[2] *Karlsruhe Institute of Technology, Karlsruhe, Germany*
[3] *Siemens, Digital Industries, Process Automation, Karlsruhe, Germany*
[4] *NXP Semiconductors Germany GmbH, Munich, Germany*

***Abstract*—The advancements in smart sensors for Industry 4.0 offer ample opportunities for low-powered predictive maintenance and condition monitoring. However, traditional approaches in this field rely on processing in the cloud, which incurs high costs in energy and storage. This paper investigates the potential of neural networks for low-power on-device computation of vibration sensor data for predictive maintenance. We review the literature on Spiking Neural Networks (SNNs) and Artificial Neuronal Networks (ANNs) for vibration-based predictive maintenance by analyzing datasets, data preprocessing, network architectures, and hardware implementations. Our findings suggest that no satisfactory standard benchmark dataset exists for evaluating neural networks in predictive maintenance tasks. Furthermore frequency domain transformations are commonly employed for preprocessing. SNNs mainly use shallow feed forward architectures, whereas ANNs explore a wider range of models and deeper networks. Finally, we highlight the need for future research on hardware implementations of neural networks for low-power predictive maintenance applications and the development of a standardized benchmark dataset.**

***Index Terms*—predictive maintenance (PM), low-power, vibration-based condition monitoring, Industry 4.0, neural networks (NNs), spiking neural networks (SNNs), artificial neural networks (ANNs), edge computing, on-device processing**

I. Introduction

Over the past years, smart sensors have been on the rise in the industry to collect data from previously uninstrumented components [1]. In addition to simple data such as temperature and humidity, acoustic data (structure-borne sound and airborne sound) are of particular interest, as they often represent the technical condition of a component [2] [3]. Using this data for Predictive Maintenance (PM) can reduce upkeep costs and increase production rates. Traditional approaches to PM generally employ a central processing instance (cloud) for analyzing the data and computing the Key Performance Indicators (KPIs). However, using a cloud instance necessitates transporting and storing high-sampled data, resulting in high energy and storage costs.

Since the energy required for data transmission is potentially more significant than the energy required for data processing, the lifetime of the sensor can increase by improving the transmission energy consumption. More energy-efficient transmission can be achieved by employing modern wireless, narrowband, and cost-effective communication channels such as the Narrowband Internet of Things (NB-IoT). Further improvements can be gained by reducing the overall amount of transmitted data. Moving the data processing from the cloud to the sensor can thus reduce the transmission requirements to only the KPIs.

II. Focused Applications

The structure-born vibrations of rotating machinery can offer meaningful information about its state of health. Those vibration signals can be utilized to identify anomalies, levels of wear and tear and other signs of faults of machines like pumps, compressors or industrial drives. For motors, the bearing condition, misalignment, and asymmetrical winding forces, e.g., due to a local short circuit, can be monitored to avoid unsuspected breakdowns or indicate the remaining useful life. Non-stationary operating machines and low rotational speeds yield vibration signals which pose a major challenge for PM.

Airborne vibrations (sound) can provide further information about the condition of machines. This approach is sensible due to the non-contact measurement and the significantly larger acoustic bandwidth. A typical disadvantage is the superimposition of ambient noise. However, depending on the number of microphones and the signal processing, it is possible to detect and localize compressed gas leaks, for example. Intelligent engine sensors equipped with MEMS microphones that keep the noise emission of an engine below a standardized limit for the health protection of personnel provide another example of the usefulness of airborne sound in PM. Other applications that benefit from the non-contact nature of sensor technology include the indication of extraneous discharges on high-voltage transformers and the condition monitoring of turbochargers driven by hot exhaust gases.

III. Sensors

The proliferation of mobile devices has significantly accelerated the growth of MEMS sensors, such as microphones, accelerometers, compasses, pressure sensors, light sensors, and capacitive touchscreens. Modern microcontrollers integrate these sensors with fast digital and wireless interfaces, simplifying device development and maintenance. Tiny boards with multiple MEMS sensors are now widely available, enhancing consumer products and other applications [4]. The adoption of Bluetooth Low Energy (BLE) wireless interfaces has further boosted this trend due to its high compatibility and market acceptance. Potential counterparts for sensor system-on-chips (SoCs) include laptops, tablets, and smartphones, all of which benefit from the low peak current demand. Energy-efficient BLE SoCs now feature ultra-low power radio transceivers [5] and long-range modes with bit coding, along with vendor-maintained security libraries. Industry vendors have also contributed to the development and early trials of these systems, often supported by smartphone apps and over-the-air firmware updates, enabling fully remote sensor operation with a gateway and cloud integration [6]. MEMS sensor performance has also advanced. For example, the [7] sensor's three-axis readout rate of 6664 Hz is well-suited for industrial applications like pump monitoring based on structure-borne noise. Its vibration transfer function remains relatively flat up to about 1000 Hz, offering good sensitivity and 16-bit sample resolution, regardless of the measurement range. MEMS digital microphones with extended frequency ranges, including ultrasound, are particularly valuable for detecting early-stage damage, such as in ball bearings [8]. In addition to countless small companies, several established process sensor suppliers [9]–[12] offer products and systems that include sensors, gateways, and cloud applications.

IV. Spiking Neural Networks

A. Fundamentals

Spiking neural networks are a biologically inspired type of neural network, which uses discrete impulses to transport information. As spikes are typically unary, with no specific value attached to them, the actual information is encoded by the timing between spikes. When there is no spike entering a neuron at a specific point in time, this neuron stays inactive and no computation is required. This makes SNNs a promising candidate for deploying AI to embedded systems.

B. Preprocessing / Event Conversion

A major challenge when using SNNs for vibration-based PM is the lack of event-based sensors. As described in Section IV-A, SNNs commonly require spikes as inputs rather than real-valued data. These spikes, outside of an SNN typically also referred to as events, should be retrieved directly from an event-based sensor for maximum efficiency. However, until now only event-based cameras have majored enough to be available as off-the-shelf components that could be used for fully event-based predictive maintenance [13]. Other sensors, such as event-based audio sensors are actively researched [14], but not yet freely available. Alternatively, events can be created by converting conventional sensor data. For this purpose, various approaches exist. They can be roughly divided into rate-based and temporal coding schemes, as shown in Fig. 1. In general, temporal coding schemes use less spikes to encode information than rate-based approaches. Less spikes require less calculation steps of the SNN used to process the event data and hence are beneficial for high energy efficiency. Auge et al. give an overview of available conversion approaches [15].

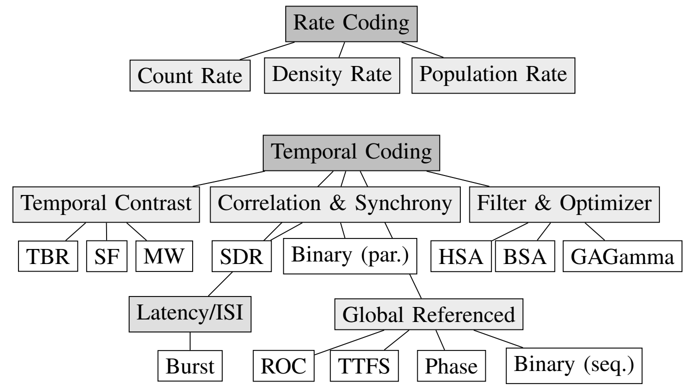

Fig. 1. Taxonomy of spike encoding techniques. Inspired by [15].

They describe the biophysical background of spike encoding and review implementations of various schemes. The specific encoding technique to use is dependent on the actual use case [16], [17]. However, there is no clear indication of which technique might be beneficial for vibration-based predictive maintenance in the state-of-the-art.

C. Approaches

The following subsection will present the most relevant approaches to Low-Power Vibration-Based Predictive Maintenance for Industry 4.0 that use Spiking Neural Networks (SNNs).

1) Ultra-low Power Machinery Fault Detection Using Deep Neural Networks [18]: The authors present a work-in-progress approach to vibration-based fault detection in centrifugal pumps (Case Western Reserve University (CWRU) dataset [19]) and bearing faults (Paderborn University Dataset (PUD) [20]). The vibration data is fed into the SNN by use of Current Injection. They employ a supervised approach to training a 4 layer Convolutional Neural Network (CNN) (input, output, two hidden layers), then convert it to a rate-coded SNN with Leaky Integrate-and-Fire (LIF) neurons using NengoDL [21].

2) Online Detection of Vibration Anomalies Using Balanced Spiking Neural Networks [22]: This approach uses balanced spiking neural networks (BSNNs) inspired by Efficient Balance Networks [23] for unsupervised, online anomaly detection using vibration sensor data from bearing faults. The authors present an implementation of the networks on the Brian2 framework [24] and the DYNAP-SE chip [25]. The data used includes the Induced Bearing Fault (IBF) dataset [26] and Run-To-Failure Bearing Fault (R2F) dataset [27]. The preprocessing pipeline includes frequency decomposition using Gammatone filter banks [28] based on the Cochlea model and an asynchronous delta modulator [29] [30] to convert the continuous values to spikes. The model consists of 3 layers (input layer, one hidden LIF layer, output layer with one output neuron). Results show a perfect confusion matrix for IBF, which detects all healthy transitions, while R2F shows earlier anomaly detection compared to state-of-the-art methods for half of the dataset.

3) Damage Detection in Structural Health Monitoring with Spiking Neural Networks [31]: This study focuses on using Long Short-Term Spiking Neural Networks (LSNNs) with Adaptive Leaky Integrate-and-Fire (ALIF) neurons for supervised damage detection tasks. The architecture consists of an input layer, connected to two recurrent ensembles, which are connected to the output layer. The study utilizes vibration sensor data from a Structural Health Monitoring (SHM) dataset obtained from a bridge subjected to SHM. The preprocessing stage consists of extracting spectral features by use of the Discrete Fourier Transform (DFT), which are then fed to the SNN by current injection. The training method uses an approximation of Backpropagation Through Time (BPTT) called E-prop [32]. Comparisons with alternative ANN models show that LSNNs have similar accuracy. The LSNN that performed the best achieved a Matthews Correlation Coefficient (MCC) of 0.88 when distinguishing between damaged and healthy bridge conditions.

4) Spiking Neural Network-Based Near-Sensor Computing for Damage Detection in Structural Health Monitoring [33]: This study presents an approach to SHM using LSNNs with 3 layers (one input, one output, one hidden recurrent with 20 ALIF neurons) trained in a supervised manner with BPTT [32]. The study further presents an implementation of the model on an STM32F407VG6 MCU SoC [34]. The paper utilizes vibration data from a SHM dataset obtained from a viaduct that underwent an intervention to strengthen its structure. The preprocessing involves spectral coefficient analysis of accelerometer waveforms, followed by an exploration of two training methods: Current-based, where Fast Fourier Transform (FFT) coefficients are applied as a constant current to input neurons, and Event-based, where FFT coefficients are transformed to spikes using a Time-to-First-Spike (TTFS) based method. The best results show a MCC ≥ 0.75.

5) A spiking neural network-based approach to bearing fault diagnosis [35]: This paper proposes a SNN-based methodology for supervised bearing fault diagnosis. It explores the use of SNNs with vibration sensor data obtained from bearing fault datasets, specifically the CWRU dataset [19] and the MFPT dataset [36]. The preprocessing includes Local Mean Decomposition (LMD) combined with population coding using Gaussian Receptive Fields (GRFs) [37] and TTFS coding. The model training uses an improved tempotron learning rule [38], which optimizes synaptic weights by minimizing the potential difference between the firing threshold and actual membrane potential. The SNN architecture consists of two LIF neuron layers (one input, one output, no hidden). Results show high accuracy, with CWRU reaching 99.17% and MFPT reaching 99.54%.

6) Research on Fault Diagnosis Based on Spiking Neural Networks in Deep Space Environment [39]: The study deals with fault diagnosis in deep space environments using SNNs in a supervised framework. The main dataset explored throughout the paper is the full life cycle data of the deep space detector bearing in the NASA database, with verification of the method being performed on the CWRU dataset [19] as well. The bearing fault data is analyzed for fault diagnosis with vibration sensors as the primary input. Preprocessing includes the time-frequency domain LMD, min-max normalization, and Gaussian population coding. Training involves the supervised training of ANNs and their conversion into SNNs. The model consists of one hidden layer with LIF neurons, one input and one output layer. Results demonstrate the efficiency of SNNs compared to traditional CNN models, showing shorter training times and high accuracy on various datasets.

7) Machine Hearing for Industrial Acoustic Monitoring using Cochleagram and Spiking Neural Network [40]: This paper investigates the application of machine hearing to industrial acoustic monitoring using SNNs for fault diagnosis, with a focusing on bearing fault detection. Data is obtained by taking 10 second acoustic measurements of a GUNT PT500 Machinery Diagnostic System [41] with each of the 6 bearing fault conditions (a normal bearing condition, a bearing condition with an outer race defect, an inner race defect, a roller element defect, and combined damages, and a bearing condition that is severely worn). The pre-processing involves the Cochleagram, which models the frequency filtering characteristics of the cochlea through Gammatone filters [28], combined with Principal component analysis (PCA) to reduce the number of frequency features from 128 to 50. The data is then encoded into spikes with population coding using neurons with GRFs and TTFS encoding. The SNN model consists of 3 layers (one input, one output, one hidden), employing a threshold-based neuron model. Training uses margin maximization techniques [42]. Results show a classification accuracy of 89.66% in detecting the bearing fault states, which is comparable to alternative techniques such as Reccurent Neural Networks (RNNs) with two Long Short-Term Memory (LSTM) layers (94.7%).

8) Efficient Time Series Classification using Spiking Reservoir [43]: This paper focuses on reservoir SNNs for fault detection applications. Using vibration data, the authors examine real-time classification datasets from the UCR repository [44], including two engine noise datasets, an inline process control measurement dataset, and a seismic dataset. Their approach compares the effectiveness of Poisson rate coding versus Gaussian temporal coding for preprocessing. The LIF-based model consists of a reservoir of 2 layers of neurons (excitatory and inhibitory). Training is performed using a supervised approach, by feeding the neuronal trace values of the excitatory neurons into a Logistic Regression based classifier that is trained with the corresponding class labels. The results show that the Gaussian temporal coding yields superior accuracy to the Poisson rate coding. Furthermore, the Gaussian temporal encoding network outperforms the IAL-Edge [45] comparison in all datasets except seismic while exhibiting performance close to that of the TN-C comparison [46].

9) A multi-layer spiking neural network-based approach to bearing fault diagnosis [47]: The study investigates multilayer SNNs. It focuses on bearing fault diagnosis of vibration data from three bearing databases, including the MFPT [36], the CWRU dataset [19], and the PUD [20]. Preprocessing includes LMD, GRFs, and Boltzmann distribution-based pulse probability sequence conversion. The model consists of a multilayer SNN with a Probabilistic Spiking Response Model (PSRM) neuron model and was trained using Backpropagation (BP). This approach outperformed existing methods regarding accuracy on all three datasets.

10) Novel Spiking Neural Network Model for Gear Fault Diagnosis [48]: In this paper, a SNN model with 2 layers (one input, one output) focused on gear fault diagnosis has been developed, by use of Spiking Response Model (SRM) neurons. The dataset used for training and testing consists of self-recorded acoustic gear fault data, with one healthy and five faulty classes. The data was pre-processed using the Slantlet Transform (SLT) to transform the time- into the frequency domain. Sixteen features were extracted, including 11 time-based features and five frequency-based features. The results showed a diagnostic accuracy of 95%.

11) Spiking Neural Networks for Structural Health Monitoring [49]: This paper explores the application of SNNs for SHM, focusing on unsupervised anomaly detection using vibration sensor data. The study uses a simulated SHM dataset generated by exciting a single-degree-of-freedom linear oscillator with Gaussian white noise forcing. Preprocessing involves using 36 Gammatone filter banks (GFBs) [28] to capture frequency characteristics, followed by spike encoding using current injection. The training uses a Neural Engineering Framework (NEF) [50] to map cepstrum features to the SNN implementation by Nengo [21]. The model consists of LIF neurons arranged in 2 layers (one input and one output layer). Results show that an averaging window of 1.5 seconds yields a clear separation between damaged and undamaged states.

12) Comparing Reservoir Artificial and Spiking Neural Networks in Machine Fault Detection Tasks [51]: This paper investigates and compares the performance of reservoir ANNs and SNNs in supervised fault detection tasks using vibration sensor data of bearing and gearbox faults. The datasets used include the ETU Bearing Dataset, the CWRU dataset [19], and a Kaggle Gearbox Fault Diagnosis Dataset [52]. Preprocessing includes spectral analysis with Short-Time Fourier transform (STFT) feature extraction. The models include Echo State Networks (ESNs) [53] and Liquid State Machines (LSMs) [54] with adaptive exponential integrate-and-fire (AdEx) neurons [55] arranged in three layers (input, one hidden reservoir, output). Despite longer execution times, SNNs show superior classification accuracy compared to ANNs.

D. Discussion

This subsection will identify and discuss the common features among the listed approaches for SNN based PM.

1) Datasets: The most commonly used dataset for benchmarking SNN performance for PM is the CWRU dataset [19], with five of the twelve approaches using it (P1, P5, P6, P9, P12). Another common approach to evaluating SNN performance, used in five papers (P3, P4, P7, P10, P11), involves creating custom datasets by recording vibration / acoustic data from various sources, like bridges, viaducts, machinery diagnostic systems and simulations. Less common datasets include the PUD [20] (used by P1 and P9), the MFPT dataset [36] (used by P5 and P9), the IBF dataset [26] (used by P2), the R2F dataset [27] (used by P2), real-time classification datasets from the UCR repository [44] (used by P8) and Kaggle Gearbox Fault Diagnosis dataset [52] (uased by P12). Proprietary datasets like the deep space detector bearing dataset in the NASA database (used by P6) and the Petersburg Electrotechnical University dataset (ETU) (used by P12) are also used.

2) Data Preprocessing: To prepare the raw vibration / acoustic data, preprocessing methods are employed. Most of the approaches employ a time-to-frequency domain conversion. Gammatone filter banks (GFBs) [28] are used in three of the papers (P2, P7, P11). Fourier Transformations are also used in three papers, but in different forms: DFT is used in P3, FFT in P4, and STFT is used in P12. LMD is used by the approaches P5, P6, P9. PCA is used in P7 and SLT is used in P10.

3) Spike Encoding: Among the presented papers, five of them (P5, P6, P7, P8, P9) employ Population Coding with Gaussian Receptive Fields (GRFs) [37]. Time-to-First-Spike (TTFS) coding is used by four approaches (P4, P5, P7, P8), as well as Current Injection (P1, P3, P4, P11). Other used methods include the asynchronous delta modulator [29] [30] (used in P2), the Poisson Rate Coding (used in P8) and the Boltzmann distribution based pulse probability sequence conversion (used in P9).

4) Neuron Models: The most widely used neuron model is the LIF (used in P1, P2, P5, P6, P8, P11). The ALIF model is employed in two papers (P3, P4), as well as the SRM model (P9, P10). The Integrate-and-Fire (IF) and AdEx models are each used in one paper only (P7 and P12 respectively).

5) SNN Architecture: The most commonly used SNN architecture is the feed forward architecture, with eight of the investigated methods using it (P1, P2, P5, P6, P7, P9, P10, P11). Two of the papers employ LSNNs (P3, P4) and two others use a Reservoir SNN approach (P8, P12).

6) Model Depth: Most of the models employ a shallow architecture, by either using only an input and an output layer (P5, P8, P10, P11), or by using an input, an output and one single hidden layer (P2, P3, P4, P6, P7, P12). Only two papers employ an architecture with two or more hidden layers (P1, P9).

7) Training: Most of the listed methods (eight out of twelve) employed a supervised approach to training the SNN (P3, P4, P5, P7, P8, P9, P10, P12), by use of some of the following approaches: BPTT / E-Prop [32], improved tempotron learning rule [38], margin maximization [42] or logistic regression applied on neuronal traces. Two of the papers (P1, P6) applied the conversion technique, by training a ANN with a supervised method, then converting it to an equivalent SNN. The remaining two papers (P2, P11) used unsupervised learning to train their networks.

TABLE I
SNN FEATURES IN REVIEWED PAPERS

Paper	Datasets	Preprocessing	Spike Encoding	Neuron Model	SNN Arch.	Layers	Training	Hardware Implementation	ANN Comparison
P1	CWRU, PUD	-	Current Injection	LIF	Feed Forward	4+	ANN Conversion	No	Yes
P2	IBF, R2F	GFBs	Async delta modulator	LIF	Feed Forward	3	Unsupervised	DYNAP-SE chip	No
P3	Custom	DFT	Current Injection	ALIF	LSNNs	3	Supervised	No	Yes
P4	Custom	FFT	Current Injection, TTFS	ALIF	LSNNs	3	Supervised	STMicroelectronics STM32F407VG6 MCU	No
P5	CWRU, MFPT	LMD	Population Coding, TTFS	LIF	Feed Forward	2	Supervised	No	No
P6	CWRU, Proprietary	LMD	Population Coding	LIF	Feed Forward	3	ANN Conversion	No	Yes
P7	Custom	GFBs, PCA	Population Coding, TTFS	IF	Feed Forward	3	Supervised	No	Yes
P8	UCR	-	Population Coding, TTFS, Poisson Rate Coding	LIF	Reservoir SNN	2	Supervised	No	Yes
P9	CWRU, PUD, MFPT	LMD	Population Coding, Boltzmann	SRM	Feed Forward	4+	Supervised	No	Yes
P10	Custom	SLT	-	SRM	Feed Forward	2	Supervised	No	No
P11	Custom	GFBs	Current Injection	LIF	Feed Forward	2	Unsupervised	No	No
P12	Proprietary, CWRU, Kaggle	STFT	-	AdEx	Reservoir SNN	3	Supervised	No	Yes

8) Hardware Implementation: From all of the listed papers, only two of them presented a hardware implementation of the proposed SNN (Approach P2: DYNAP-SE chip [25], Approach P4: STMicroelectronics STM32F407VG6 MCU system-on-chip [34]).

9) ANN comparison: Seven papers present their results by comparing them with ANNs for the same task (P1, P3, P6, P7, P8, P9, P12).

E. Patents

Reviewing existing patent applications reveals a need for more descriptions of deploying SNNs for anomaly detection or Predictive Maintenance (PM) in industrial environments.

In [56], the authors describe a system that generates and analyzes a sensor data stream to detect anomalies during a machine's operation. The system comprises one or more sensors, a computation unit with a memory device, and a communication interface. In order to detect anomalies during operation, an ANN or an SNN is trained with sensor data from a new machine under regular operating conditions. Subsequently, the system is employed to identify instances of behavior that diverge from the training operation patterns.

In [57], SNNs are integrated into a comprehensive industrial equipment fault prediction and health monitoring system. The system encompasses several submodules, including anomaly detection, fault analysis, and correction mechanisms. The anomaly detection and fault analysis are based on a broad collection of sensor information, including temperature, pressure, noise, vibration, strain, crack, wear, and corrosion. Furthermore, the approach fuses image identification and nondestructive testing to analyze crack, wear, and corrosion damages.

V. ARTIFICIAL NEURAL NETWORKS

A. Predictive Maintenance with Artificial Neural Networks

Research in ANN-based PM can be categorized by system architecture, purpose, and approach [58]. The primary system architectures include Open System Architecture for Condition-based Monitoring, cloud-enhanced PM, and PM 4.0. PM 4.0 provides support for technicians through online analysis of collected data. The Open System Architecture for Condition-based Monitoring, as defined in ISO 13374, offers a standardized, layered framework for PM design and implementation. Cloud-enhanced PM leverages the potential of cloud computing with a centralized architecture.

From a methodological standpoint, approaches can be classified into three main categories: knowledge-based, traditional Machine Learning (ML), and Deep Learning (DL)-based techniques. Knowledge-based methods rely on expert knowledge and experience with system faults. Traditional ML and DL differ primarily in the number of hidden layers within the Neural Network (NN). While ML uses big data to learn highly nonlinear functions and generalize from similar situations, shallow ANNs with fewer units and hidden layers struggle to extract hidden information from raw data and require manual feature engineering [58]. Consequently, DL methodologies are typically favored.

The most prominent DL methods are Auto-Encoder (AE), CNN, and Deep Belief Network (DBN) whereby recurrent architectures are used to keep a memory of the past [58], [59]. Instead of directly applying raw sensor data as input for the DL approach, the sensor measurements are preprocessed and transformed into time, frequency, or time-frequency domain to extract features.

Recent reviews focus on the general application of DL methods in PM with a focus on architecture, structure, and purpose [58]. A comprehensive survey on PM in industry 4.0 is provided in [60] and with a particular focus on cloud or fog computing in [61]. The application of PM for bearing fault detecting is considered in [59], [62]. The authors provide an overview of the advances regarding bearing fault diagnosis with DL methods. In [63], the authors present a survey about fault detection and diagnosis for induction motors. DL methods for engine failure prediction are reviewed in [64].

B. Approaches Emphasizing Low Power

In [65], the authors apply a two-stage low-power and in-sensor anomaly detection. The architecture is divided into a hardware AE and a software CNN part. The AE is always on at the sensor and detects anomalies. Once an anomaly is detected, the CNN is activated and serves as a classifier based on the encoder part of the AE. The results reveal that the system achieves high accuracy with an anomaly detection rate of 99.61% on the CWRU dataset and very low power consumption of the AE when implemented on a Xilinx Artix 7 FPGA with 122mW while operating at the maximum frequency of 45MHz.

A sensor-fusion PM utilizing vibration and sound data for a brushless direct current motor is proposed in [66]. The PM system is deployed on an FPGA in order to allow close hardware-software collaboration and hardware-accelerated algorithms for fault detection. The authors investigated the usability of a CNN, an LSTM, and a combination of both for PM besides the comparison of vibration and sound data. The results generally show that sound information outperforms the vibration in a single-sensor setup, but the accuracy improves with data-level sensor fusion. The CNN model significantly outperforms the LSTM model. Combining both models is better than single LSTM but less accurate than CNN. The results indicate that the LSTM has to be used with a feature extraction step in advance [66].

A smart vibration sensor for industrial applications with integrated ultra-low power embedded PM is proposed in [67]. An unsupervised K-means algorithm based on feature extraction is used for monitoring and failure detection. The algorithm is embedded on an ARM M4F with an average power consumption of $80\mu W$ and leads to one year of battery life with a single CR2032 battery cell.

A decentralized on-device ML approach to identify patterns in sensor data is demonstrated in [68]. The approach comprises a framework for distributed sensor networks to shift the computation from the cloud to the edge devices. A CNN Bi-Directional LSTM model for fault prognosis in machines of industry 4.0 is proposed in [69]. The method allows the analysis of machine characteristics based on embedded sensors. The model is evaluated on the Machine Investigation and Inspection (MIMII) dataset [70] with reliability over 94%.

In [71], the end-to-end multichannel CNN condition monitoring and fault detection framework DeepWind for wind turbines is presented. The DeepWind framework exploits multi-channel CNN and can be implemented on resource-constrained embedded devices. It detects faults in rotor blades in wind turbines based on automatic feature detection and subsequent classification. First, the raw sensor data is downsampled and windowed in a software preprocessing step. Afterward, the data is transformed into the frequency domain and fed into an embedded Mulit-Channel CNN. The applied CNNs have 50 and 40 filters with kernel sizes of 8 and 4. The system is evaluated on a real wind turbine dataset with a fault detection average of 94%.

A study on developing, testing, and evaluating ML approaches for low-cost microcontrollers is presented in [72]. The authors analyze the current state of the art regarding low-power PM applications on the edge. The focus is on algorithms that can be trained and run on limited memory resource devices with online model parameter adaption. The underlying goal is to avoid needing a separate backend and additional communication.

A self-contained low-power on-device PM (LOPdM) system based on a self-powered sensor is elaborated in [73]. Compared to traditional PM systems where the data is transmitted to and processed in a server, the data is locally inferred with low power consumption in the TinyML-based PM system. A dataset with a self-powered sensor from a simulated vibration environment is collected and used for model evaluation. In the evaluation, random forest and Deep Neural Network (DNN) model showed the highest accuracy.

In [74], the authors present Eciton, a low-power LSTM accelerator for PM systems with low-power edge-sensor nodes. Eciton shows the power consumption of 17mW under load and reduces memory and chip resources utilizing 8-bit quantization and sigmoid activation function. The accelerator fits on a low-power Lattice iCE40 UP5K FPGA and demonstrates real-time processing with minimal loss of accuracy. The proposed method is evaluated on two publicly available datasets, a turbofan engine maintenance dataset from NASA [75] and an electrical motor maintenance dataset with vibration and humidity data [76].

A workflow for training a quantized DL anomaly detection for devices with limited memory, compute, and power resources is described in [77]. A Deep Support Vector Data Description (SVDD) model is used for edge computing to overcome the drawback of large AE composed of an encoder and decoder, resulting in many layers. The detection performance of the SVDD model is evaluated in terms of AUC on the MIMII dataset. The proposed SVDD model outperforms traditional AEs and reduces the computational complexity by 50%.

An online low-power signal processing algorithm for fault detection based on frequency data is shown in [78]. The algorithm can improve the detection of small amplitudes at fault representing frequencies without complex signal processing and is therefore suitable for on-device applications.

C. Discussion

A comparison of different approaches with regard to characteristic features is shown in Table II. Most approaches use custom data recorded with individual sensors to evaluate their proposed approach. Two approaches use the MIMII dataset, one approach the CWRU, and one approach a turbofan engine dataset from NASA as well as an electrical motor dataset. A common pre-processing technique across the reviewed paper is to transform the time series data into the frequency domain using Fourier Transformation. For this, either a FFT or a STFT is used. Additionally, the input data can be windowed to process the data in patterns. This can also be used to obtain a fixed input size for the ANN. As network architecture, AE and recurrent approaches are often used. All recurrent approaches use an LSTM to process time series data and keep track of the history. Convolutional operations are used to extract features. Either as part of the AE or as an additional feature extractor. 7 out of 8 approaches are trained in a supervised manner and one in an unsupervised. None of the approaches compares the performance of the ANN with an SNN approach.

D. Patents

The survey is extended to patents publications in the field of ANNs with an emphasis on low-power predictive maintenance applications. Two patent specifications are published that disclose applications in the given context.

In [79], the authors propose the TinyML technology [80] for use in predictive maintenance applications. The goal of the development is the shift of data processing from the cloud to the edge to enhance data efficiency. With a single-chip microcomputer as the computation platform, the authors achieve a low-cost and low-power ANN deployment to analyze industrial equipment on the edge.

In [81], the patent claim in [79] is extended with kinetic energy harvesting to promote a durable application without the need for external energy. In this regard, the authors deploy a piezoelectric sensor as the information source and the main energy supply. Consequently, the invention allows for the application in extreme environments with limited energy resources, in which changing the battery causes additional efforts.

VI. ANN-SNN Comparison

A comparison between the two fundamental approaches can be made based on the papers analyzed in this work concerning both SNNs IV and ANNs V. The most common method to evaluate performance is to create custom datasets. The most used publicly available dataset for both approaches is the CWRU dataset [19]. The most widely employed preprocessing method for SNNs and ANNs is a transformation from the time domain to the frequency domain. The most used SNN architecture is a simple Feed Forward, with few approaches employing more complex structures such as LSNNs or Reservoirs. On the other hand, ANNs employ various strategies such as CNN, LSTM, and Feed Forward equally. One possible reason may be the inherent recurrent nature of SNNs resulting from the stateful neuron units. SNNs more often employ shallow architectures (1-3 layers), whereas ANNs focus on deeper models (4+). This could be due to the challenges associated with training of deep SNNs. The vast majority of all the approaches present a supervised training method.

VII. Conclusion

The paper's main objective is to explore the use of Neural Networks (NNs) for low-power Predictive Maintenance (PM) in Industry 4.0. The motivation for this work stems from some of the drawbacks of the traditional approaches to PM, which include the high transmission and storage costs of analyzing sensor data in the cloud.

This work reviews the existing literature on Spiking Neural Networks (SNNs) for PM concerning training datasets, preprocessing, spike encoding, neuron models, SNN architecture, layer depth, training methods, and hardware implementations. The analysis extends to the most prominent Artificial Neuronal Network (ANN) approaches regarding datasets, preprocessing, network architecture and models, depth, training methods, and hardware implementation. A comparison between ANNs and SNNs finds that both approaches often use the same preprocessing methods, primarily focused on transformations from the time domain to the frequency domain. ANN models and architectures are more diverse, exploring a mix of CNNs, LSTM, and Feed-Forward models with deeper networks. In contrast, SNN approaches mainly employ Feed-Forward architectures and shallow networks. The comparison also finds no agreement towards a standard benchmark dataset for predictive maintenance within or across the two fundamental methods. Limited information is available regarding hardware implementations for both methods.

This paper suggests that future research in low-power PM should focus on practical hardware implementations of neural networks. Furthermore, since most of the analyzed methods recoursed to creating custom datasets, it suggests that a standard benchmark for low-power predictive maintenance is needed.

Disclosure

We employed grammar-checking software to identify and correct grammatical errors, typos, and stylistic inconsistencies (Grammarly [82], DeepL Write [83]).

Acknowledgments

This research is funded by the German Federal Ministry of Education and Research as part of the project "ThinKIsense", funding no. 16ME0564.

TABLE II
ANN FEATURES IN REVIEWED PAPERS

Paper	Datasets	Preprocessing	Activation	Architecture	ANN Model	Layers	Training	Hardware Implementation
[65]	CWRU	No	ReLU	Classifier, AE	CNN	6	Supervised	Xilinx Artix 7 FPGA
[66]	Custom	Raw data segmentation	ReLU	Classifier, Recurrent	CNN, CNN-LSTM, LSTM	5+	Supervised	FPGA
[67]	Custom	FFT	-	Classifier	-	-	Unsupervised	TI CC2652
[69]	MIMII	LPC	ReLU	Classifier, Recurrent	CNN-LSTM	8	Supervised	-
[71]	Custom	Windowing, FFT	-	Classifier	CNN, Feed Forward	5	Supervised	FPGA
[73]	Custom	FFT	ReLU	Classifier	Feed Forwad	1-4	Supervised	ESP32 -Tensilica Xtensa LX6
[74]	NASA [75], Electric motor [76]	-	Sigmoid, Tanh	Accelerator, Recurrent	LSTM	3-4	Supervised	Lattice iCE40 UP5K FPGA
[77]	MIMII	STFT	ReLU, Linear	Classifier, AE	Feed Forward, SVDD	6	Supervised	-

REFERENCES

[1] “Smart Sensors Market - Forecast, Share & Growth.” [Online]. Available: https://www.mordorintelligence.com/industry-reports/global-smart-sensors-market-industry

[2] M. Vishwakarma, R. Purohit, V. Harshlata, and P. Rajput, “Vibration analysis & condition monitoring for rotating machines: a review,” *Materials Today: Proceedings*, vol. 4, no. 2, pp. 2659–2664, 2017.

[3] G. Jombo and Y. Zhang, “Acoustic-based machine condition monitoring—methods and challenges,” *Eng*, vol. 4, no. 1, pp. 47–79, 2023.

[4] “STMicroelectronics.” [Online]. Available: https://diolan.com/st

[5] “EFR32BG27 Series 2 Small Bluetooth LE SoC - Silicon Labs.” [Online]. Available: https://www.silabs.com/wireless/bluetooth/efr32bg27-series-2-socs

[6] “TIDC-CC2650STK-SENSORTAG reference design TI.com.” [Online]. Available: https://www.ti.com/tool/TIDC-CC2650STK-SENSORTAG

[7] “LSM6DSL - iNEMO 6DoF inertial measurement unit (IMU), for smart phones and battery operated IoT, Gaming, Wearable and Consumer Electronics. Ultra-low power and high accuracy - STMicroelectronics.” [Online]. Available: https://www.st.com/en/mems-and-sensors/lsm6dsl.html

[8] “Knowles Ultrasonic MEMS Microphone.” [Online]. Available: https://www.knowles.com/resource-news-details/new-product-ultrasonic-mems-microphone

[9] “SITRANS SCM IQ.” [Online]. Available: https://www.siemens.com/global/en/products/automation/process-instrumentation/digitalization/smart-condition-monitoring.html

[10] “Condition Monitoring for rotating equipment - Motor condition monitoring| ABB Motion Services - ABB Motion Services | Data and Advisory services (ABB Motion Services).” [Online]. Available: https://new.abb.com/service/motion/data-and-advisory-services/condition-monitoring-for-rotating-equipment

[11] “Honeywell Versatilis™ Transmitter | Honeywell.” [Online]. Available: https://process.honeywell.com/us/en/products/field-instruments/honeywell-versatilis-equipment-health-monitoring-ehm-solutions/honeywell-versatilis-transmitter

[12] Y. E. Corporation, “XS770A Wireless Vibration Sensor,” 2019. [Online]. Available: https://web-material3.yokogawa.com/13/23403/file_name/GS01W06E01-01EN.pdf

[13] X. Li, S. Yu, Y. Lei, N. Li, and B. Yang, “Intelligent machinery fault diagnosis with event-based camera,” *IEEE Transactions on Industrial Informatics*, vol. 20, no. 1, pp. 380–389, 2024.

[14] C. Lenk, P. Hövel, K. Ved, S. Durstewitz, T. Meurer, T. Fritsch, A. Männchen, J. Küller, D. Beer, T. Ivanov *et al.*, “Neuromorphic acoustic sensing using an adaptive microelectromechanical cochlea with integrated feedback,” *Nature Electronics*, vol. 6, no. 5, pp. 370–380, 2023.

[15] D. Auge, J. Hille, E. Mueller, and A. Knoll, “A survey of encoding techniques for signal processing in spiking neural networks,” *Neural Processing Letters*, vol. 53, no. 6, pp. 4693–4710, 2021.

[16] C. D. Schuman, J. S. Plank, G. Bruer, and J. Anantharaj, “Non-traditional input encoding schemes for spiking neuromorphic systems,” in *2019 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2019, pp. 1–10.

[17] C. Schuman, C. Rizzo, J. McDonald-Carmack, N. Skuda, and J. Plank, “Evaluating encoding and decoding approaches for spiking neuromorphic systems,” in *Proceedings of the International Conference on Neuromorphic Systems 2022*, 2022, pp. 1–9.

[18] S. Nitzsche, M. Neher, S. von Dosky, and J. Becker, “Ultra-low power machinery fault detection using deep neural networks,” in *Machine Learning and Principles and Practice of Knowledge Discovery in Databases*, ser. Communications in Computer and Information Science. Springer International Publishing, 2021, pp. 390–396.

[19] K. Loparo, “Case western reserve university bearing data center,” *Bearings Vibration Data Sets, Case Western Reserve University*, pp. 22–28, 2012.

[20] Konstruktions- und antriebstechnik (KAt) - bearing DataCenter(universität paderborn). [Online]. Available: https://mb.uni-paderborn.de/kat/forschung/kat-datacenter/bearing-datacenter

[21] T. Bekolay, J. Bergstra, E. Hunsberger, T. DeWolf, T. C. Stewart, D. Rasmussen, X. Choo, A. R. Voelker, and C. Eliasmith, “Nengo: a python tool for building large-scale functional brain models,” *Frontiers in neuroinformatics*, vol. 7, p. 48, 2014.

[22] N. Dennler, G. Haessig, M. Cartiglia, and G. Indiveri, “Online detection of vibration anomalies using balanced spiking neural networks,” in *2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS)*. IEEE, 2021, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/document/9458403/

[23] R. Bourdoukan, D. Barrett, S. Deneve, and C. K. Machens, “Learning optimal spike-based representations,” *Advances in neural information processing systems*, vol. 25, 2012.

[24] M. Stimberg, R. Brette, and D. F. Goodman, “Brian 2, an intuitive and efficient neural simulator,” *elife*, vol. 8, p. e47314, 2019.

[25] S. Moradi, N. Qiao, F. Stefanini, and G. Indiveri, “A scalable multicore architecture with heterogeneous memory structures for dynamic neuromorphic asynchronous processors (dynaps),” *IEEE transactions on biomedical circuits and systems*, vol. 12, no. 1, pp. 106–122, 2017.

[26] E. Bechhoefer, “Condition based maintenance fault database for testing diagnostics and prognostic algorithms,” *MFPT Data*, 2013.

[27] H. Qiu, J. Lee, J. Lin, and G. Yu, “Wavelet filter-based weak signature detection method and its application on rolling element bearing prognos-

tics," *Journal of sound and vibration*, vol. 289, no. 4-5, pp. 1066–1090, 2006.

[28] R. PATTERSON, "An efficient auditory filterbank based on the gammatone function," *Meeting of the IOC Speech Group on Auditory Modelling at RSRE, 1987*, 1987. [Online]. Available: https://cir.nii.ac.jp/crid/1570291225803648384

[29] F. Corradi and G. Indiveri, "A neuromorphic event-based neural recording system for smart brain-machine-interfaces," *IEEE transactions on biomedical circuits and systems*, vol. 9, no. 5, pp. 699–709, 2015.

[30] M. Sharifshazileh, K. Burelo, J. Sarnthein, and G. Indiveri, "An electronic neuromorphic system for real-time detection of high frequency oscillations (hfo) in intracranial eeg," *Nature communications*, vol. 12, no. 1, p. 3095, 2021.

[31] L. Zanatta, F. Barchi, A. Burrello, A. Bartolini, D. Brunelli, and A. Acquaviva, "Damage detection in structural health monitoring with spiking neural networks," in *2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT)*. IEEE, 2021, pp. 105–110. [Online]. Available: https://ieeexplore.ieee.org/document/9488476/

[32] G. Bellec, F. Scherr, A. Subramoney, E. Hajek, D. Salaj, R. Legenstein, and W. Maass, "A solution to the learning dilemma for recurrent networks of spiking neurons," *Nature communications*, vol. 11, no. 1, p. 3625, 2020.

[33] F. Barchi, L. Zanatta, E. Parisi, A. Burrello, D. Brunelli, A. Bartolini, and A. Acquaviva, "Spiking neural network-based near-sensor computing for damage detection in structural health monitoring," *Future Internet*, vol. 13, no. 8, p. 219, 2021. [Online]. Available: https://www.mdpi.com/1999-5903/13/8/219

[34] "STM32F407VG - High-performance foundation line, Arm Cortex-M4 core with DSP and FPU, 1 Mbyte of Flash memory, 168 MHz CPU, ART Accelerator, Ethernet, FSMC - STMicroelectronics." [Online]. Available: https://www.st.com/en/microcontrollers-microprocessors/stm32f407vg.html

[35] L. Zuo, L. Zhang, Z.-H. Zhang, X.-L. Luo, and Y. Liu, "A spiking neural network-based approach to bearing fault diagnosis," *Journal of Manufacturing Systems*, vol. 61, pp. 714–724, 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0278612520301138

[36] "Fault Data Sets." [Online]. Available: https://www.mfpt.org/fault-data-sets/

[37] Q. Yu, H. Tang, K. C. Tan, and H. Yu, "A brain-inspired spiking neural network model with temporal encoding and learning," *Neurocomputing*, vol. 138, pp. 3–13, 2014.

[38] R. Gütig and H. Sompolinsky, "The tempotron: a neuron that learns spike timing–based decisions," *Nature neuroscience*, vol. 9, no. 3, pp. 420–428, 2006.

[39] R. Li and J. Yuan, "Research on fault diagnosis based on spiking neural networks in deep space environment," in *2022 3rd Asia Service Sciences and Software Engineering Conference*. ACM, 2022, pp. 165–170. [Online]. Available: https://dl.acm.org/doi/10.1145/3523181.3523205

[40] Y. Zhang, S. Dora, M. Martinez-Garcia, and S. Bhattacharyaand, "Machine hearing for industrial acoustic monitoring using cochleagram and spiking neural network," in *2022 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE, 2022, pp. 1047–1051. [Online]. Available: https://ieeexplore.ieee.org/document/9863412/

[41] "Pt 500 machinery diagnostic system." [Online]. Available: https://www.gunt.de/index.php?option=com_gunt&task=gunt.list.category&product_id=1022&lang=en&Itemid=148

[42] S. Dora and N. Kasabov, "Spiking neural networks for computational intelligence: an overview," *Big Data and Cognitive Computing*, vol. 5, no. 4, p. 67, 2021.

[43] S. Dey, D. Banerjee, A. M. George, A. Mukherjee, and A. Pal, "Efficient time series classification using spiking reservoir," in *2022 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2022, pp. 1–8. [Online]. Available: https://ieeexplore.ieee.org/document/9892728/

[44] H. A. Dau, A. Bagnall, K. Kamgar, C.-C. M. Yeh, Y. Zhu, S. Gharghabi, C. A. Ratanamahatana, and E. Keogh, "The ucr time series archive," *IEEE/CAA Journal of Automatica Sinica*, vol. 6, no. 6, pp. 1293–1305, 2019.

[45] A. Pal, A. Ukil, T. Deb, I. Sahu, and A. Majumdar, "Instant adaptive learning: An adaptive filter based fast learning model construction for sensor signal time series classification on edge devices," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2020, pp. 8339–8343.

[46] P. Malhotra, V. TV, L. Vig, P. Agarwal, and G. Shroff, "Timenet: Pre-trained deep recurrent neural network for time series classification," *arXiv preprint arXiv:1706.08838*, 2017.

[47] L. Zuo, F. Xu, C. Zhang, T. Xiahou, and Y. Liu, "A multi-layer spiking neural network-based approach to bearing fault diagnosis," *Reliability Engineering & System Safety*, vol. 225, p. 108561, 2022. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0951832022002095

[48] Y. H. Ali, F. Y. H. Ahmed, A. M. Abdelrhman, S. M. Ali, A. A. Borhana, and R. Ishak Raja Hamzah, "Novel spiking neural network model for gear fault diagnosis," in *2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA)*. IEEE, 2022, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9935414/

[49] G. V. Joseph and V. Pakrashi, "Spiking neural networks for structural health monitoring," *Sensors*, vol. 22, no. 23, p. 9245, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/23/9245

[50] C. Eliasmith and C. H. Anderson, *Neural engineering: Computation, representation, and dynamics in neurobiological systems*. MIT press, 2003.

[51] V. Kholkin, O. Druzhina, V. Vatnik, M. Kulagin, T. Karimov, and D. Butusov, "Comparing reservoir artificial and spiking neural networks in machine fault detection tasks," *BDCC*, vol. 7, no. 2, p. 110, 2023. [Online]. Available: https://www.mdpi.com/2504-2289/7/2/110

[52] "Gearbox Fault Diagnosis." [Online]. Available: https://www.kaggle.com/datasets/brjapon/gearbox-fault-diagnosis

[53] C. Gallicchio and A. Micheli, "Tree echo state networks," *Neurocomputing*, vol. 101, pp. 319–337, 2013.

[54] W. Maass, T. Natschläger, and H. Markram, "Real-time computing without stable states: A new framework for neural computation based on perturbations," *Neural computation*, vol. 14, no. 11, pp. 2531–2560, 2002.

[55] R. Brette and W. Gerstner, "Adaptive exponential integrate-and-fire model as an effective description of neuronal activity," *Journal of neurophysiology*, vol. 94, no. 5, pp. 3637–3642, 2005.

[56] "Predictive maintenance of components used in machine automation." [Online]. Available: https://worldwide.espacenet.com/patent/search/family/079586302/publication/US2022026879A1?q=US2022026879A1

[57] "Industrial equipment fault prediction and health monitoring system." [Online]. Available: https://worldwide.espacenet.com/patent/search/family/083670292/publication/CN115238915A?q=pn%3DCN115238915A

[58] Y. Ran, X. Zhou, P. Lin, Y. Wen, and R. Deng, "A survey of predictive maintenance: Systems, purposes and approaches," 12.12.2019.

[59] D.-T. Hoang and H.-J. Kang, "A survey on deep learning based bearing fault diagnosis," *Neurocomputing*, vol. 335, pp. 327–335, 2019.

[60] Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0," *Sustainability*, vol. 12, no. 19, p. 8211, 2020.

[61] A. Angelopoulos, E. T. Michailidis, N. Nomikos, P. Trakadas, A. Hatziefremidis, S. Voliotis, and T. Zahariadis, "Tackling faults in the industry 4.0 era-a survey of machine-learning solutions and key aspects," *Sensors (Basel, Switzerland)*, vol. 20, no. 1, 2019.

[62] S. Schwendemann, Z. Amjad, and A. Sikora, "A survey of machine-learning techniques for condition monitoring and predictive maintenance of bearings in grinding machines," *Computers in Industry*, vol. 125, p. 103380, 2021.

[63] M. Drakaki, Y. L. Karnavas, I. A. Tziafettas, V. Linardos, and P. Tzionas, "Machine learning and deep learning based methods toward industry 4.0 predictive maintenance in induction motors: State of the art survey," *Journal of Industrial Engineering and Management*, vol. 15, no. 1, p. 31, 2022.

[64] S. Namuduri, B. N. Narayanan, V. S. P. Davuluru, L. Burton, and S. Bhansali, "Review—deep learning methods for sensor based predictive maintenance and future perspectives for electrochemical sensors," *Journal of The Electrochemical Society*, vol. 167, no. 3, p. 037552, 2020.

[65] P. Vitolo, G. D. Licciardo, L. Di Benedetto, R. Liguori, A. Rubino, and D. Pau, "Low-power anomaly detection and classification system based on a partially binarized autoencoder for in-sensor computing," in *2021 28th IEEE International Conference on Electronics, Circuits, and Systems (ICECS)*. IEEE, 2021, pp. 1–5.

[66] P. Suawa, T. Meisel, M. Jongmanns, M. Huebner, and M. Reichenbach, "Modeling and fault detection of brushless direct current motor by deep

learning sensor data fusion," *Sensors (Basel, Switzerland)*, vol. 22, no. 9, 2022.
[67] Sebastián Marzetti, Valentin Gies, Valentin Barchasz, Hervé Barthélemy, and Hervé Glotin, "Ultra-low power embedded unsupervised learning smart sensor for industrial fault detection," *2020 IEEE International Conference on Internet of Things and Intelligence System (IoTaIS)*, 2022.
[68] H. Ren, D. Anicic, and T. A. Runkler, "The synergy of complex event processing and tiny machine learning in industrial iot," in *Proceedings of the 15th ACM International Conference on Distributed and Event-based Systems*, A. Margara and E. Della Valle, Eds. ACM, 2021, pp. 126–135.
[69] V. Justus and G. R. Kanagachidambaresan, "Machine learning based fault-oriented predictive maintenance in industry 4.0," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 1, pp. 462–474, 2022.
[70] H. Purohit, R. Tanabe, K. Ichige, T. Endo, Y. Nikaido, K. Suefusa, and Y. Kawaguchi, "Mimii dataset: Sound dataset for malfunctioning industrial machine investigation and inspection," 2019.
[71] G. M. Hassan, A. Rahil, R. Sneha, M. Suraj, K. Maurice, and P. J. Felix, *DEEPWIND: An Accurate Wind Turbine Condition Monitoring Framework via Deep Learning on Embedded Platforms*. Piscataway, NJ: IEEE, 2020.
[72] M. Grethler, M. B. Marinov, and V. Klumpp, "Embedded machine learning for machine condition monitoring," in *Future Access Enablers for Ubiquitous and Intelligent Infrastructures*, ser. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, D. Perakovic and L. Knapcikova, Eds. Springer International Publishing, 2021, vol. 382, pp. 217–228.
[73] Z. Chen, Y. Gao, and J. Liang, "Lopdm: A low-power on-device predictive maintenance system based on self-powered sensing and tinyml," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–13, 2023.
[74] J. Chen, S. Hong, W. He, J. Moon, and S.-W. Jun, "Eciton: Very low-power lstm neural network accelerator for predictive maintenance at the edge," in *2021 31st International Conference on Field-Programmable Logic and Applications (FPL)*. IEEE, 2021, pp. 1–8.
[75] A. Saxena, K. Goebel, D. Simon, and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," *International Conference on Prognostics and Health Management*, 10 2008.
[76] J. Moon, P. Lindahl, J. Donnal, S. Leeb, L. Zachar, L. Cotta, and C. Schantz, "A nonintrusive magnetically self-powered vibration sensor for automated condition monitoring of electromechanical machines," in *2016 IEEE AUTOTESTCON*, 09 2016, pp. 1–7.
[77] B. Boons, M. Verhelst, and P. Karsmakers, "Low power on-line machine monitoring at the edge," in *2021 International Conference on Applied Artificial Intelligence (ICAPAI)*. IEEE, 2021, pp. 1–8.
[78] B. Asad, H. A. Raja, T. Vaimann, A. Kallaste, R. Pomarnacki, and K. van Hyunh, "A current spectrum-based algorithm for fault detection of electrical machines using low-power data acquisition devices," *Electronics*, vol. 12, no. 7, p. 1746, 2023.
[79] "Tinyml-based ultra-low power consumption high-reliability end-side predictive maintenance system." [Online]. Available: https://worldwide.espacenet.com/patent/search/family/086698360/publication/CN115941729A?q=pn%3DCN115941729A
[80] P. P. Ray, "A review on tinyml: State-of-the-art and prospects," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 4, pp. 1595–1623, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1319157821003335
[81] "Passive predictive maintenance system based on tinyml and kinetic energy collection technology." [Online]. Available: https://worldwide.espacenet.com/patent/search/family/086446015/publication/CN116184900A?q=pn%3DCN116184900A
[82] "Grammarly." [Online]. Available: https://app.grammarly.com/
[83] "DeepL Write: AI-powered writing companion." [Online]. Available: https://www.deepl.com/write