A Self-powered Predictive Maintenance System Based on Piezoelectric Energy Harvesting and TinyML

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Abstract—Nowadays, the Industrial Internet of Things (IIoT) plays a more and more significant role in smart manufacturing. Predictive Maintenance (PdM) is one of the essential applications, recognizing the current status of the machine and preventing disastrous breakdowns. End-point sensors for such monitoring systems are powered mainly by batteries. As IIoT grows, constantly replacing batteries across thousands of devices is cost-prohibitive. In addition, tremendous original sensing data are wirelessly transmitted to the server for data analysis, causing colossal energy consumption. In this paper, we propose the first self-powered on-device PdM system based on piezoelectric energy harvesting and tiny machine learning (TinyML). A trained TinyML model is deployed on the low-cost microcontroller (MCU) for on-device inferring; only the diagnosis result is wirelessly transmitted to the server for data analysis, causing prohibitive. In addition, tremendous original sensing data are wirelessly transmitted to the server for data analysis, causing prohibitive. In addition, tremendous original sensing data are wirelessly transmitted to the server for data analysis, causing prohibitive. In addition, tremendous original sensing data are wirelessly transmitted to the server for data analysis, causing prohibitive.

I. INTRODUCTION

With the development of the Industrial Internet of Things (IIoT), factories are placing higher demands on pervasive machine monitoring, and maintenance [1]. Since the impact of maintenance represents a total of 15 to 60% of all operational costs in the manufacturing industry [2], an efficient maintenance strategy proves significant in solving machine anomalies. Predictive maintenance (PdM) is a superior technique that triggers the corresponding necessary maintenance measures only when needed or just before, avoiding shutdown in the production processes and minimizing maintenance costs [3]. The most fundamental part of a PdM system is to identify the current state of the equipment in real time.

Machine learning (ML) models have proved the outstanding performance in PdM [4]. However, most end-point sensors are regarded as data tubes transmitting all the original data to the remote server, which relies on the resource-rich and power-hungry device for artificial intelligence (AI) model training and inferring. Such systems may lead to undesired data privacy issues and large energy consumption. Researchers have focused on deploying ML models at the edge in recent years [5]. Tiny machine learning (TinyML), a booming branch of state-of-the-art ML techniques, enables the low-cost MCU to run on-device ML models at a milliwatt-level power consumption without real-time support of large servers [6]. Yet, TinyML is still at a very early age. More application-specific studies based on TinyML are needed.

Replacing and repairing batteries for the exponentially increasing number of IIoT end-point devices is labor-intensive and environmental-unfriendly [7]. Energy Harvesting (EH), trying to transform the ambient energy from wasted to useful, proves a promising technology for battery-free IoT (Internet of Things) [8]. As the kinetic energy harvesting (KEH) based solution booms, some cyber-electro-mechanical co-design have been proposed for ubiquitous IoT, ignoring the effects of the volatile light radiation and radio frequency signals [9]. However, systematic KEH-IoT designs are few in academia and industry due to the interdisciplinarity of mechanical, electrical, and computer knowledge [10]. In addition, many KEH-IoT approaches are proposed for easy application, such as beacon counting and temperature sensing. To further increase the efficiency of the self-sustained systems, some studies paid attention to simultaneously energy harvesting and sensing (SEHS) [11], which means the harvester serves a self-powered sensor (SPS) to substitute the commercial sensor, such as the inertial measurement unit (IMU).

To the best of our knowledge, an interdisciplinary study for PdM with TinyML, energy harvesting, and SEHS remains unexplored. In this paper, we propose a self-powered TinyML-based PdM system where the harvester works as both an energy source and an SPS, emphasizing ultra-low-power and low-cost end-point intelligence. It brings a promising solution for pervasive sensing and ubiquitous AI.

II. RELATED WORK

PdM is a cutting-edge strategy to predict severe malfunctions in factory machines, ensuring the smooth operation of production line [3], thus decreasing the high costs resulting from unpredictable machine downtime and defective products [2]. It is based on the fact that many devices have a detectable
Energy harvesting is an emerging technology enabling self-powered devices like MCUs to infer original data at the endpoint with an ML algorithm [6]. The efficiency of TinyML enables a plethora of battery-powered, always-on applications that can revolutionize the real-time collection and processing of data [15]. In [16], an intelligent rail vehicle running states monitoring system based on TinyML and IMU is proposed.

Energy harvesting is an emerging technology enabling self-maintained IoT devices. As a cyber-electro-mechanical co-design, leveraging the energy harvester as a power source and a sensor has recently attracted increasing interest. ETHG [17], a system based on triboelectric nanogenerators and electromagnetic generators, is proposed to realize self-powered IoT nodes for remote collection of wind speed and direction. In [18], a KEH-based pavement roughness estimation system is presented with SEHS ability. Yet, many KEH-based SEHS systems use different harvesters as energy and information sources, respectively, with increased cost or use the relationship between energy and information to achieve perception with low sensitivity.

Given the challenges above, the proposed self-sustained PdM system utilized only one energy harvester for powering and sensing with an embedded TinyML technique for on-device inferring and similar vibration diagnosis.

### III. System Overview

Fig. 1 shows the architecture of the proposed self-powered TinyML-based PdM system. A piezoelectric cantilever as an energy source, as well as SPS, is utilized to capture vibration energy, substitute commercial IMU, and form an intelligent end device with a well-designed energy management circuit and a low-cost MCU. Since the energy generated from the tiny vibration is still insufficient to support the MCU’s stable operation, the capacitor inside the circuit first stores the converted energy from the harvester. While embedded with the UVLO (under-voltage lockout) function, the energy management circuit can sense the voltage of the capacitor and turn on the MCU when the stored energy is sufficient, ensuring all operations are completed.

A voltage signal is generated from the base-excited SPS, reflecting the current vibration information. First, The real-world data for different machine statuses are collected with a low sampling rate for saving energy and used for pre-training a TinyML model. When the specific abnormal information can be obtained handily in advance, the PdM system can not only identify both the occurrence of the anomaly and the specific abnormal situation. After deploying the compressed model on an MCU, the end device can carry out the intelligent evaluation. A low-power BLE SoC-based minimum system with a transceiver and CPU is chosen as the MCU. It starts running when the energy is sufficient. Given the awareness of intermittent operation, the software program is set to allow the MCU only to run the necessary parts, including initializing, sensing, processing, inferring, and transmitting. After on-device inference, the current machine state is identified and reported to the near receiver within 1 second with low power consumption. Subsequently, when the circuit senses that the energy consumption has reached a certain level, the MCU would be cut off until the next running cycle. The machine information can be sent to the cloud server for remote monitoring according to the application requirements. The vibration energy and information are fully utilized in this system with EH and TinyML techniques for self-contained end-point intelligence.

### IV. Working Principle

To realize a cyber-electro-mechanical co-design, a lost-cost, well-rounded energy management circuit is designed for stable intermittent operation and SEHS. Utilizing the piezoelectric energy harvester as a data source and TinyML as a data inferring method, the system achieves end-point intelligence efficiently.

#### A. Simultaneously energy harvesting and sensing

Fig. 2(a) shows a piezoelectric cantilever that generates a voltage according to the vibration. One end of the cantilevered beam is fixed on the vibrating structure, usually called the base. The other end is free and mounted with a tip mass.
As the machine vibrates, the beam is simultaneously excited by the vibrating base. At the open-circuit condition, the piezoelectric patch subsequently generates a voltage \( v_p(t) \), which is proportional to the beam deflection \( x(t) \) with a ratio of \( \alpha \), i.e.,

\[
v_p(t) = \alpha x(t).
\]  

(1)

Intermittent operation is proven to be the better executing mode for KEH-based IoT systems [10]. A comprehensive board-level energy-aware circuit, incorporating rectification, energy storage, and voltage regulation functions, is designed and utilized to manage the energy and realize the intermittency in computing regarding [19], as shown in Fig. 2(b). Two threshold voltages, \( V_{start} \) and \( V_{close} \), can be conveniently changed by adjusting the resistor network, realizing low-power analog UVLO. Moreover, this circuit offers a comparably stable regulated output voltage to power the IoT devices while requiring no additional quiescent current skillfully using a depletion-mode MOSFET [19].

A piezoelectric transducer can be considered an SPS. For a common IMU-based sensing method, the generated three-axis data is transmitted to an MCU through an I^2C bus. For a self-powered sensing approach, one-axial vibration data is generated without any extra power supply, thus decreasing the power consumption for sensing. For realizing simultaneously energy harvesting and sensing, there exist three challenges:

1) **Common ground problem during sensing:** We use the analog-to-digital converter (ADC) inside the MCU for voltage sensing. Since the piezoelectric sheet generates alternating current, a common choice for rectification is the full bridge rectifier circuit. However, the harvester and MCU are not co-grounded, which leads to huge signal distortion. Thus in this design, we use a diode for half-wave rectifying and a diode for the continuity of the equivalent capacitance current of the piezoelectric sheet, as shown in Fig. 2(b). We intend to sacrifice some energy harvesting efficiency for more significant sensing accuracy.

2) **Connection between SPS and ADC:** For SEHS, the ADC is connected to the SPS for original voltage sensing. Due to the characteristic of ADC, half-wave voltage is cut in this way. Since we have used a half-wave rectifier circuit, this problem is acceptable. However, if the ADC is connected directly to the harvester, it will take away part of the generated energy, decreasing energy harvesting efficiency. We connected two same large megohm resistors in parallel, as shown in Fig. 2(b), allowing only small signals to flow into the ADC.

3) **Signal distortion:** Considering the extra cost and power consumption of adding an auxiliary circuit for sensing both positive and negative half-cycle signals, in this study, we simply drop the negative half-cycle signals. Furthermore, we intend to sense the signal at a low sampling rate with small data for energy saving, which leads to considerable data distortion. With advanced ML models, the distortion can be well compensated.

**B. TinyML Development and Deployment**

As mentioned above, TinyML equips the IIoT end devices with basic intelligence. Fig. 3 illustrates the TinyML pipeline of the proposed system, including end device sampling, data preprocessing, model training, and model deploying. The SPS is used to capture the vibration information from the equipment. To further reduce the power consumption, the lower the sampling rate of MCU for data acquisition, the better. Subsequently, the real-world data goes through some preprocessing methods, such as data normalization and missing value imputation. For traditional ML, the model is built with the open-source scikit-learn library and trained with the processed data. Then the model is converted by advanced inference frameworks, such as micromlgen. After being converted into a document suitable for embedded systems, the lightweight models are easily deployed to the TinyML-supported MCUs for on-device monitoring from the real-time SPS signals.

**C. On-device Intermittent Operation**

EH-based IoT devices primarily work intermittently. Fig. 4 demonstrates the energy picture for the proposed battery-
There are two basic phases: 1) charging; and 2) sensing, computing, and transmitting. In the beginning, the stored energy is close to the off threshold. As the energy keeps flowing into the storage capacitor, the stored energy accumulates. It is the charging period when the IoT device is turned off. When the energy reaches the turn-on threshold, the IoT device is turned on to execute necessary tasks. The energy consumption of the IoT device can be measured, denoted as $E_c$. As the MCU finishes the scheduled tasks, the stored energy drops quickly and reaches the off threshold. Thus $t_{\text{compute}}$ is generally much smaller than $t_{\text{charge}}$. If the machine stays in a stable frequency, the interval of one round operation is a rough constant. Repeatedly, the IoT device would be turned off and wait until the energy is sufficient.

After measuring the total energy consumed by the MCU for one round of necessary operation, we can derive the minimal energy required for each interval, i.e., $E_c$. According to the energy formula

$$E_c = \frac{1}{2} C \left( V_{\text{start}}^2 - V_{\text{close}}^2 \right),$$

the harvested energy in each round can be set as small as possible by taking $E_c$ as a reference and handily adjusting the on/off threshold voltages of the energy management circuit. This balance of supply and demand is critical for highly-efficient battery-free IoT systems.

V. EXPERIMENT

To comprehensively evaluate the performance of the proposed system, we have conducted several experiments. A rich SPS data set is built and analyzed by five well-known supervised ML models, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and K-Nearest Neighbor (KNN). The proposed system is prototyped, and the performance is validated. The specifications of the system are listed in Table I.

### TABLE I

<table>
<thead>
<tr>
<th>Unit</th>
<th>Component</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td>harvester</td>
<td>Soft beam</td>
</tr>
<tr>
<td></td>
<td>Material</td>
<td>Copper</td>
</tr>
<tr>
<td></td>
<td>Size</td>
<td>$10\times80\times0.3$ mm$^3$</td>
</tr>
<tr>
<td>Proof mass</td>
<td>Weight</td>
<td>13g</td>
</tr>
<tr>
<td>Circuit</td>
<td>Energy-aware</td>
<td>Resistance</td>
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<tr>
<td></td>
<td>circuit</td>
<td>Capacitance</td>
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<tr>
<td>Sampling</td>
<td>circuit</td>
<td>Resistance</td>
</tr>
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<td>MCU</td>
<td>nRF52832</td>
<td>nRF52832</td>
</tr>
<tr>
<td>Software</td>
<td>nRF5 SDK V17.1</td>
<td></td>
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The anomaly information is particular in each maintenance problem [20]. In addition, there is no publicly available SPS-based dataset for simulation experiments. Therefore, in this study, we use a vibration platform to simulate a working machine and collect multiple data sets. The experimental setup for data acquisition and performance analysis is shown in Fig. 5. A cantilevered piezoelectric energy harvester is installed on the vibration source, controlled by a computer-based vibration controller (computer #1). The test PCB integrates the circuit shown in Fig. 2(b) and an off-the-shelf nRF52832 minimal system board. As the platform oscillates, the generated energy flows into the energy management circuit. For data acquisition, the MCU is separated and battery-powered, transmitting real-time digital values to another computer (computer #2) at 40 Hz, 60 Hz, and 80 Hz with 12-bit precision through a CH340 module. Since the voltage of the capacitor is set to the threshold voltage of 3.3 V every time the MCU is powered on, we control the amplitude of the piezoelectric energy harvester at 3.3 V and start sampling data after the capacitor voltage is stabilized. A piezoelectric sheet collects the most energy when the vibration reaches its resonant frequency. However, as mentioned, every machine may have different vibration status, so it is not fair and general to simulate a vibration in resonant frequency. The prototyped harvester’s resonant frequency is 24.8 Hz. So we choose 20 Hz vibration as a normal state, while a 0 Hz one is regarded as in the idle state. Vibration signals at 19 and 21 Hz are regarded as two specific abnormal conditions. Note that We strictly control the same amplitude of the voltage generated by the piezoelectric sheet for the three vibration cases, i.e., 4.2 V. Thus, we can only identify these data according to the frequency information.
Due to the space limit, the fast Fourier transform (FFT) is not shown. The result shows that they all look nearly the same, which means an expert system building for the small SPS data size will cost a certain amount of effort. Although this distorted signal is hard to analyze using a simple algorithm, we can still use the efficient TinyML technology for realizing the on-device inferring.

**B. Machine Learning Analysis**

Given the challenges of the distorted SPS signal, we intend to use five ML algorithms for analysis, including DT, RF, SVM, LR, and KNN. ML models are based on the default settings of the sklearn library, and the results are based on 5-fold cross validation.

Fig. 7(a) shows the accuracy of different models for data length ranging from 1 to 20 on a quadruple classification case. RF model is set to be ten decision trees with gini criterion. Considering the tradeoff between accuracy and power consumption, the 60 Hz sampling rate is preferred. Since the model has an ultra-high recognition ability for different machine states, when unknown anomalies occur, the MCU will have a relatively low confidence rate, which means the MCU can also accurately discern the occurrence of unknown anomalies with a simple threshold setting.

**C. Performance validation**

Fig. 8(a), (b), and (c) show the waveform under the frequencies of 19 Hz, 20 Hz, and 21 Hz, respectively. The on and off threshold voltages of the system are set to 3.1 V and 2 V, respectively, while the regulated output voltage is set to 2.8 V. From the waveform, we can see the system is working intermittently as originally designed. The software code of the EUU is optimized to only broadcast two BLE beacon packets in one round after completing initializing, sensing, preprocessing, and inferring. As we can see, the difference in performance is evident.
between the beacon intervals in three similar vibration statuses is ultra-small. By simply counting the interval between received wireless packets, the current machine status is hard to deduce. With TinyML, we successfully receive the correct beacon in different vibration statuses within 20 meters.

VI. CONCLUSION

This paper proposed a self-powered TinyML-based PdM system with an emphasis on ultra-low power and low-cost end-point intelligence. TinyML equipped the end machine with intelligence for perceiving its situation in real time, thus relieving the tight dependency on high-end servers. By knowing the minimal power consumption of one round of computational tasks, we have set the on/off thresholds of the energy-aware circuit to realize a balance between supply and demand. To further reduce power consumption, the piezoelectric energy harvester was utilized as both an energy and information source, realizing SEHS. A rich SPS dataset was collected with a vibration platform and analyzed by five well-known ML models. Random forest algorithm identified raw SPS signal with 99% accuracy when the required data length and sampling rate were 5 and 60 Hz, respectively. Experiments were carried out to validate the availability and performance. After a thorough design from EH, sensing, analyzing, intermittent operation mode, etc., the system can reliably fulfill condition-based PdM. This cyber-electro-mechanical co-design is hoped to provide valuable inspiration for future ubiquitous AIoT studies.

REFERENCES