Long-Lifetime Event-Driven Wireless Monitoring System for Pole-Mounted Transformers

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Abstract: As smart grids develop rapidly, low-cost monitoring systems for pole-mounted transformers increase in demand. Even though battery-powered wireless monitoring systems appear to provide optimal solutions, they consume large amounts of energy for continuous sampling and data transmission. Operation and maintenance costs then increase owing to reduced battery lifetime and battery replacement. To overcome this problem, this paper presents an event-driven battery-powered wireless monitoring system that monitors abnormalities of a transformer and transmits data only if an abnormality occurs. When the proposed event controller detects an abnormality, it enables a root mean square (RMS) converter and a peak detector for sampling and transmitting the maximum RMS value of the abnormal signal and then falls into sleep mode until the next event to save energy. Simulation and experimental results show that the proposed system enhances battery lifetime by up to two orders of magnitude compared to a conventional battery-powered wireless monitoring system.

Keywords: abnormality monitoring; battery powered; pole-mounted transformer; event driven; root mean square (RMS)

1. Introduction

Power transformers are one of the most vital components in power systems for substation operations and safety of electricity [1]. Figure 1 shows several physical quantities caused by various electrical faults in power transformers carrying high AC voltages and large currents [2-5]. A sudden failure can be very costly, not only for replacement, but also in terms of power outage-related problems for consumers [6]. As smart grids develop rapidly, enhancement of their reliability increases in demand. Thus, it is necessary to monitor and diagnose the state of transformers continuously, to timely detect incipient transformer problems, and to plan maintenance and repair or replacement [7].

Conventional monitoring systems for large-scale power transformers have been developed using wired monitoring components. Wired sensors are widely adopted for high-speed continuous data acquisition (DAQ) of raw data from physical quantities of transformers such as bushing failures [8,9], winding deformation [10,11], partial discharge [12], and valve malfunctions [13]. For pole-mounted transformers, however, a high-speed DAQ system can be a bulky and very expensive solution [14]. Remote methods using infrared thermographs or ultrasonic fault detection have been introduced for monitoring pole-mounted transformers with limited accessibility or safety hazards [15,16]. Even though the equipment for remote monitoring can be expensive, multiple transformers at different locations can be monitored using a single remote monitoring unit. However, skilled specialists need to be present on-site to analyze the performance, which eventually leads to higher operation and maintenance (O&M) costs [17]. Recently, battery-powered wireless real-time monitoring systems have been widely developed for monitoring pole-mounted power transformers at a lower cost and with a smaller size [18-22]. As the sampling rate required to acquire the physical quantities as raw data can be too high for low-cost.
devices, the raw signal from a sensor needs to be converted into a root mean square (RMS) value that quantifies the physical or electrical parameters of the input signal [14,23]. An RMS criterion is directly related to the load applied to the sensor and provides a suitable measurement quantity for any monitoring application [14]. In [23], an RMS value from a piezoelectric sensor quantified the amount of partial discharge (PD) in power transformers. However, continuous sampling and data transmission of the converted RMS value using conventional monitoring systems severely shorten battery lifetime, owing to the large energy requirement.

To overcome this problem, this paper proposes a long-lifetime wireless monitoring system that provides low-cost real-time solutions. The proposed event controller (EC) monitors the abnormality of the input and allows for event-driven sampling when an abnormality is present in a transformer. The maximum RMS value for a given abnormality is obtained using an RMS converter followed by a peak detector. The proposed EC enables or disables each block and determines when to sample and transmit data. Without an abnormal signal, most of the components fall into sleep mode, waiting for the next abnormality. As a result, the battery lifetime of the proposed monitoring system can be two orders of magnitude higher than that of a conventional monitoring system without an EC.

2. Conventional Monitoring Systems
2.1. Types of Conventional Monitoring Systems

Figure 2a shows a simplified block diagram of a conventional wired monitoring system for large-scale power transformers. In the monitoring system of a power transformer, various physical quantities can be converted into electrical signals using sensors, such as PD, vibration, and ultrasound. When an electrical signal is fed to a signal conditioner through a wire, the signal conditioner manipulates the input to prepare it for the next stage, a high-speed DAQ. The DAQ output is collected in a data center for monitoring and diagnosis. Even though this high-speed and real-time monitoring system is accurate and reliable, it cannot be applied to monitor pole-mounted transformers with limited accessibility or safety hazards, due to its high cost and large size. Before smart grid technologies were developed, noncontact-based remote sensors such as ultrasound and thermal imagers were widely used for monitoring pole-mounted transformers, as shown in Figure 2b. High-frequency signals such as ultrasonic or acoustic emissions can be received by a remote sensor, followed by a filter as a signal conditioner, and then an audible frequency converter (AFC) that converts a high-frequency input signal to a lower audible frequency so that a specialist can analyze it by its sound. Even though the output signal needs to be analyzed by skilled specialists on-site, multiple remote locations can be monitored with only a single set of portable monitoring units. However, there are several drawbacks to this remote monitoring system. As the number of pole-mounted transformers to be monitored increases, more specialists are needed for regular checkups. Furthermore, real-time monitoring for each pole-mounted transformer is not supported because of the lack of a network. Even though it is possible to realize real-time monitoring...
by adding a network for remotely acquired data, the additional cost cancels out the benefits of remote monitoring.

To accomplish real-time monitoring of pole-mounted transformers at a low cost, wireless monitoring has been developed as shown in Figure 2c [25]. Once a physical signal from a power transformer is detected by a sensor, a signal conditioner reduces noise and is followed by a DAQ. A wireless transmitter (TX) communicates the output of the DAQ to a receiver (RX). To realize small and low-cost solutions for real-time monitoring that enable long-term data transmission and analysis, battery-powered monitoring systems based on Internet-of-Things (IoT) devices can provide good solutions. However, continuous monitoring and data transmission using a wireless monitoring system consumes a large amount of energy, necessitating frequent replacement of batteries, resulting in higher O&M costs.

2.2. Conventional Battery-Powered Wireless Monitoring

Figure 3a shows a basic battery-powered wireless monitoring system in a noisy environment, with a band-pass filter (BPF) as a signal conditioner [19–22,25]. The BPF input $v_{SN}$ is defined as

$$v_{SN}(t) = v_S(t) + v_N(t),$$

where $v_S$ and $v_N$ are the sensor output and noise, respectively. Assuming that $v_N$ is white noise, the output signal of the BPF, $v_{IN}$, can be expressed as

$$v_{IN}(t) = v_S(t) + v_{NF}(t),$$

where $v_{NF}$ is the filtered noise. This $v_{IN}$ is fed to an analog-to-digital converter (ADC) with high sampling frequency $f_H$. Assume the abnormal input is an intermittent continuous signal with $i$th lower and upper time bounds $t_{Li}$ and $t_{Ui}$, respectively, as depicted in Figure 3b.
A monitoring system requires a large number of samples; in fact, the sampling frequency $f_H$ must be higher than the Nyquist rate of $v_{IN}$. The energy required for monitoring the $i$th intermittent abnormal input sampled at $f_H$, $E_B(f_H)$, can be calculated as

$$E_B(f_H) = [P(BPF) + P(ADC(f_H)) + P(TX(f_H))](t_{L(i+1)} - t_{Li}),$$

where $P(X)$ is the average power consumption of block $X$. The power consumption in an ADC and TX can be functions of $f_H$. As the minimum sampling speed is limited by the Nyquist rate, $f_H$ cannot be decreased to reduce energy consumption. Therefore, to lower energy consumption, it is critical to have a signal conditioner that converts an input to another form that allows for a reduced sampling rate without degrading the physical significance of the input. The RMS value is one of the most important criteria for evaluating the signal acquired by various sensors, including PD and acoustic emission [26–28]. Adding an RMS converter to the signal conditioner, as depicted in Figure 4a, the output of the RMS converter, $v_{RMS}$, can be expressed as

$$v_{RMS}(t) = RMS(v_{IN}(t)) = \sqrt{\frac{1}{t - t_L} \int_{t_L}^{t} v_{IN}^2(\tau) d\tau},$$

where $RMS(x(t))$ is the RMS value of $x$ from the lower time bound $t_L$ to $t$.

The frequency of $v_{RMS}$ can be lower than that of $v_{IN}$ by the integration, which means the sampling frequency of the RMS output, $f_L$, can be much lower than $f_H$ ($f_H > 2f_{VIN} > f_L > 2f_{VRMS}$), as shown in Figure 4b. Note that $f_{VIN}$ and $f_{VRMS}$ are the frequencies of the

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**Figure 3.** Conventional high-speed monitoring system with a band-pass filter (BPF) as a signal conditioner. (a) Block and (b) timing diagrams with noise.

**Figure 4.** Conventional low-speed monitoring system with RMS converter. (a) Block and (b) timing diagrams.
signals $v_{IN}$ and $v_{RMS}$, respectively. Thus, the energy consumption for the $i$th intermittent abnormal input using an RMS converter sampled at $f_L$, $E_{RMS}(f_L)$, can be expressed as

$$E_{RMS}(f_L) = [P(BPF) + P(RMS) + P(ADC(f_L))] \cdot \left( t_{Li(i+1)} - t_{Li} \right) \tag{5}$$

As the provided condition $P(RMS) + P(ADC(f_L)) + P(TX(f_L)) < P(ADC(f_H)) + P(TX(f_H))$ is satisfied, from (3) and (5), $E_{RMS}$ can be lower than $E_{Bi}$.

### 3. Proposed Event-Driven Monitoring System

To extract a physical quantity of an abnormal input in conventional wireless monitoring systems, an ADC and TX need to make multiple samplings and data transmissions for each intermittent abnormal input. This results in high energy consumption because all the components are turned on all the time. As suggested by (3) and (5), energy consumption can be reduced by using the proposed EC, as shown in Figure 5a.

**Figure 5.** Conventional monitoring system with proposed event controller (EC). (a) Block and (b) timing diagrams, with sampling time delay $t_D$.

The EC minimizes the turn-on time of each block while continuously monitoring the input. In addition, it employs event-driven data sampling and transmission that allows only one sample for each intermittent abnormal period, as depicted in Figure 5b, and makes the power consumption of the ADC and TX independent of sampling frequency. When an $i$th abnormal input is sensed at $t = t_{Li}$, the BPF and RMS converter generate the signal $v_{RMS}$ based on $v_{IN}$ until $v_{RMS}$ becomes zero at $t = t_{Ui}$. After a time delay $t_D$, the ADC and TX are enabled by the EC for their normal operating times $t_{ADC}$ and $t_{TX}$, respectively. Then, each block falls into sleep mode when disabled; the power consumption in sleep mode is negligible compared to that in normal mode. The energy consumption for a conventional wireless monitoring system with an RMS converter and EC, $E_{ECi}$, can be approximated as

$$E_{ECi} \approx P(EC) \left( t_{Li(i+1)} - t_{Li} \right) + [P(BPF) + P(RMS)] \cdot (t_{Ui} - t_{Li}) + P_{ADC}t_{ADC} + P_{TX}t_{TX} \tag{6}$$

In the conventional monitoring system shown in Figure 4a, the BPF and RMS converter are always-on blocks. However, the proposed EC reduces the normal operation time for each block, with $t_{Ui} - t_{Li}$, $t_{ADC}$, and $t_{TX}$ being much smaller than $t_{Li(i+1)} - t_{Li}$ for the $i$th intermittent abnormal input. Therefore, the energy consumption of the BPF, RMS converter, ADC, and TX can be greatly reduced. As long as $P(EC)(t_{Li(i+1)} - t_{Li})$ is small enough to be neglected, $E_{ECi}$ can be lower than $E_{RMS}(f_L)$ in (5). However, the uncertainty of whether the maximum value of $v_{RMS}$ occurs at time $t_D$ reduces the signal-to-noise ratio (SNR) of the
overall monitoring system. The SNR of the conventional monitoring system with EC in Figure 5a, for the $i$th intermittent abnormal input, $\text{SNR}_{\text{ECi}}$, can be expressed as

$$\text{SNR}_{\text{ECi}} = \frac{P(\text{RMS}(v_S(t_{Li} + t_D)))}{P(\text{RMS}(v_{\text{NF}}(t_{Li} + t_D)))},$$

where $\text{RMS}(x(t))$ is the RMS value of $x$ from the lower time bound $t_{Li}$ to $t$, with $t_{Li} \leq t \leq t_{Ui}$. As $v_{\text{NF}}(t)$ is Gaussian noise with a mean of zero and is not correlated with $v_S(t)$, $\text{RMS}(v_{\text{NF}}(t_{Li} + t_D))$ can be assumed to be constant regardless of $t_D$, leading to

$$\text{SNR}_{\text{ECi}} \approx \alpha \left[ \text{RMS}(v_S(t_{Li} + t_D)) \right]^2,$$

where $1/\alpha$ is the noise power. As $\text{RMS}(v_S(t_{Li} + t_D))$ varies with $v_S$ and $t_D$, $\text{SNR}_{\text{ECi}}$ cannot be guaranteed to have its maximum value at the time of sampling.

To guarantee that the maximum RMS value is transmitted, a peak detector is attached after the RMS converter in the proposed monitoring system shown in Figure 6a.

![Figure 6. Proposed event-driven monitoring system. (a) Block and (b) timing diagrams.](image)

Unlike the previous conventional system with proposed EC in Figure 5a, this system samples the maximum RMS value using the peak detector and holds its value until $v_{\text{RMS}}$ becomes zero at $t = t_{Ui}$ as shown in Figure 6b. Then, the SNR of the proposed monitoring system for the $i$th intermittent abnormal input, $\text{SNR}_{\text{Propi}}$, can be approximated as

$$\text{SNR}_{\text{Propi}} \approx \alpha [\text{Max}(\text{RMS}(v_S(t)))]^2,$$

If the maximum RMS value is obtained at $t = t_M$, it can be rewritten as

$$\text{SNR}_{\text{Propi}} \approx \alpha [\text{RMS}(v_S(t_M))]^2,$$

This indicates that $\text{SNR}_{\text{Propi}}$ is always equal to or larger than $\text{SNR}_{\text{ECi}}$. Although local peaks can exist, the proposed monitoring system stores only the global maximum value for each intermittent abnormal input to maximize the SNR.

The proposed monitoring system takes advantage of event-driven sampling and data transmission, yielding just one sample per abnormal input to reduce sampling and thus energy consumption. The energy consumption of the proposed system for the $i$th intermittent abnormal input, $E_{\text{Propi}}$, can be expressed as

$$E_{\text{Propi}} = E_{\text{ECi}} + P(\text{PEAK})(t_{Ui} - t_{Li}),$$

where $P(\text{PEAK})$ is the power consumption of the peak detector.

Figure 7a shows the circuit diagram of the proposed event-driven monitoring system in detail. A passive BPF that does not require power can be used to lower energy consump-
tion. The enable signals generated by the EC set each block—the RMS converter, peak detector, ADC, and TX—to fall into either normal or sleep mode. The EC is composed of three comparators, a D flip-flop, an AND gate, and two capacitors with reset switches. \( \text{CMP}_1 \) operates at high speed to detect abnormalities over a wide frequency range, but \( \text{CMP}_2 \) and \( \text{CMP}_3 \) can be low-speed and low-power comparators that only reset the enable signals. For event-driven enable controls, the EC needs to be always on to monitor input abnormalities. The timing diagram of the proposed monitoring system is shown in Figure 7b. It has four phases. In phase I, an abnormality in the input is detected by \( \text{CMP}_1 \) when \( v_{\text{IN}} > V_{\text{REF1}} \). Then, the generated clock pulse \( C_K \) triggers a D flip-flop and sets \( \text{EN}_{\text{RMS}} \) high to turn on both the RMS converter and the peak detector until \( \text{CMP}_2 \) and \( \text{CMP}_3 \) detect the conditions \( v_{\text{PEAK}} > v_{\text{RMS}} \) and \( v_{\text{RMS}} < V_{\text{REF2}} \). The increment in \( v_{\text{RMS}} \) is proportional to \( C_1 \), which works as a low-pass filter; \( v_{\text{PEAK}} \) is stored in \( C_2 \). In phase II, the ADC is enabled to sample \( v_{\text{PEAK}} \) after disabling both the RMS converter and the peak detector. Thereafter, the digital value \( D_O \) of \( v_{\text{PEAK}} \) is delivered to the TX. In phase III, after finishing sampling, the ADC generates an end-of-conversion (EOC) signal that enables the TX and resets \( C_1 \) and \( C_2 \). Finally, the output of the TX, \( D_{\text{OUT}} \), is generated by adding a wireless communication protocol to \( D_O \). In phase IV, after finishing transmission, all blocks except the EC fall into sleep mode; the EC continues to monitor abnormality in the input.

Figure 7. Proposed monitoring system. (a) Detailed circuit and (b) timing diagram.
4. Simulation Results

Measuring an abnormal signal from an active and healthy power transformer can be not only time consuming but also potentially dangerous. To assess the effectiveness of the proposed monitoring system for a pole-mounted transformer, a PD signal was chosen as an input for monitoring and was modeled using an experimental jig, as shown in Figure 8 [29]. A function generator supplied an AC input to a power amplifier, producing a 22 kV AC input, which was fed to needle electrodes in an oil-filled can to mimic a PD signal. This signal was sensed using a PD sensor attached to the bottom of the can, and its transient waveform was stored using an oscilloscope, as shown in Figure 9a.

![Experimental jig for modeling the PD in a pole-mounted transformer.](image)

**Figure 8.** Experimental jig for modeling the PD in a pole-mounted transformer. (a) Schematic diagram for the jig and (b) experimental setup.

![Mimicked PD signal and its fitted curve.](image)

**Figure 9.** PD signal from the PD generator. (a) Mimicked PD signal and its fitted curve and (b) fast Fourier transform of the mimicked PD signal.

MATLAB was used to generate the Simulation Program with Integrated Circuit Emphasis (SPICE) simulation program with the PD signal as an input, extracting a fitted curve composed of eight single-tone sine waves given by

\[
f(t) = \sum_{n=1}^{8} a_n \sin(b_n t + c_n),
\]  

(12)
where the coefficients $a_n$, $b_n$, and $c_n$ are listed in Table 1. The fast Fourier transform of the PD input in Figure 9b exhibits dominant frequencies in several MHz bands.

| n | $a_n$ (V) | $b_n$ (MHz) | $c_n$ (Radian) |
|---|---|---|---|
| 1 | 106.7147 | 4.69 | $-0.7276$ |
| 2 | 70.4558 | 5.08 | 1.7639 |
| 3 | 54.6218 | 3.13 | $-2.0701$ |
| 4 | 50.9293 | 4.30 | 2.7057 |
| 5 | 47.04 | 2.34 | $-3.1245$ |
| 6 | 40.5062 | 3.52 | 1.1196 |
| 7 | 40.3764 | 3.91 | $-1.4116$ |
| 8 | 33.9337 | 1.95 | 0.3388 |

In this study, the Cadence Spectre with TSMC 0.18 μm process parameters was used for SPICE simulation. The control circuit timing diagram is shown in Figure 10. The peak voltage of the fitted input was set to 1 V. Other parameters were set as follows: $V_{\text{REF1}} = 0.4 \text{ V}$, $V_{\text{REF2}} = 0.1 \text{ V}$, $C_1 = 10 \text{ pF}$, and $C_2 = 10 \text{ pF}$.

![Figure 10. Simulated waveforms in the proposed monitoring system.](image)

The basic operation of this circuit is identical to that shown in Figure 7b. The 3 dB pass band for the BPF was set to 100 Hz–50 MHz. Noise $v_N$ in (1) was assumed to be a white noise source in the Cadence Spectre simulation. Figure 11 shows simulated SNR results for a conventional system with the proposed EC and event-driven monitoring system. As $t_D$ is an ad hoc parameter that varies according to the input signal, it was set to a Gaussian random variable with a mean of $(t_{U_i} + t_{L_i})/2 - t_{L_i}$ and variance of 1 μs for the $i$th intermittent abnormal input. A total of 1,000,000 iterations were used for validating the ranges of the SNRs in the conventional system with EC and using the proposed method, $\text{SNR}_{\text{EC}}$ and $\text{SNR}_{\text{Prop}}$, respectively. $\text{SNR}_{\text{EC}}$ is shown with error bars, the average value indicated by a square. $\text{SNR}_{\text{Prop}}$ is always equal to or greater than $\text{SNR}_{\text{EC}}$ for any noise level. At $\text{RMS}(v_N) = 27.68 \text{ mV}$, $\text{SNR}_{\text{Prop}}$ is greater than the average value of $\text{SNR}_{\text{EC}}$ by 12.93 dB, and greater than the minimum value of $\text{SNR}_{\text{EC}}$ by 135.42 dB.
**Figure 11.** Simulated SNR variation with RMS value of input noise in a conventional monitoring system with the event controller ("EC"), and with the proposed event-driven monitoring system ("Prop").

### 5. Experimental Results

The prototype printed circuit board (PCB) of the proposed monitoring system and its experimental setup are shown in Figure 12. The PCB measures 5.4 cm × 3.1 cm with a vertically integrated RF communication module FS1000A as TX. Table 2 lists the model name of each commercially available block used.

![Prototype PCB](image1.png) ![Experimental setup](image2.png)

**Figure 12.** Experimental setup for the proposed system. (a) Prototype PCB and (b) experimental setup with PD signal as input.

| **Table 2.** Model name of each block of the proposed system. |
| --- | --- | --- | --- | --- | --- |
| **CMP** | **RMS Converter** | **Peak Detector** | **ADC** | **TX** |
| Model name | TS331 | TLV7011 | LTC1968 | LTC6244 | AD7787 | HT12E, FS1000A |

Figure 13 shows the experimental results for each transient waveform of the proposed monitoring system: \( v_{IN}, v_{RMS}, v_{PEAK}, E_{RMS}, E_{OC}, \) and \( D_{OUT} \). The PD signal in Equation (12) and Table 1 was applied by a function generator controlled by ArbExpress software, and is shown in Figure 14a. From the zoomed-in view at the top of Figure 13, it
can be seen that $EN_{RMS}$ is set to be high for 33.6 $\mu$s immediately after $v_{IN}$ becomes higher than $V_{REF1}$. The peak value of $v_{RMS}$ is obtained once $v_{IN}$ sets to zero after the propagation delay set by $C_1$. From $EOC$ and $D_{OUT}$, $t_{ADC}$ and $t_{TX}$ are obtained as 1.2 ms and 2.8 ms, respectively. The RF communication module exhibits 1.4 ms latency at the transmission frequency of 100 kHz. For further quantification, three more input waveforms (a pure sine wave, a sine wave with linearly decaying amplitude, and a triangular wave) were generated as intermittent abnormal inputs lasting only 4.0 $\mu$s at 5.0 MHz, as shown in Figure 14b–d, respectively. Figure 15 compares the linearity of $v_{PEAK}$ with respect to the RMS input for the four different input signals. The RMS value of each input was obtained by controlling its peak voltage from 0.5 V to 1.5 V. The maximum integral nonlinearity (INL) and offset of each input waveform are listed in Table 3, which was obtained using a MATLAB curve-fitting tool.

Figure 13. Experimental results for transient waveforms in the proposed event-driven monitoring system. (a) Detecting $v_{PEAK}$ out of $v_{RMS}$ and (b) its data transmission.
Figure 14. Input signals used for experiments. (a) Generated PD signal, (b) pure sine wave, (c) sine wave with linearly decaying amplitude, and (d) triangular wave.

Figure 15. Experimental results showing variation of $v_{\text{PEAK}}$ with RMS input for various waveforms.

Table 3. Model name of each block of the proposed system.

|                | Sine Wave Amplitude Decaying | Triangular Wave | Generated PD |
|----------------|-----------------------------|-----------------|--------------|
| Offset (mV)    | 236.50                      | -188.10         | -4.13        | 2.18         |
| Maximum INL (%)| 2.76                        | 9.05            | 3.81         | 4.44         |

To compare the energy demands of different wireless monitoring systems, the energy consumption of each block for a conventional system without the proposed EC, and for the proposed event-driven system, was analyzed. The results are shown in Figure 16, where the abnormality occurs at a frequency of 60 Hz. As shown in Figure 16a, the conventional system always runs in normal mode with a total energy consumption of 26.5 mWs. In contrast, most of the proposed system operates either in normal or sleep modes; only the EC is always on, as shown in Figure 16b. The power consumption of other blocks in normal mode is always higher than that in sleep mode by several orders of magnitude. Therefore, to reduce energy consumption, it is critical to keep all possible components...
of the proposed monitoring system in sleep mode as long as possible. For each block, the run-time in sleep mode is several orders longer than in normal mode, except for the always-on EC. As a result, the total energy consumption in the proposed event-driven monitoring system is as low as 1.75 mWs. In Figure 17, the measured energy consumption in this system is compared to the calculated energy consumption based on the datasheets of the components, as the frequency of abnormality occurrence is varied.

Figure 16. Measured power and energy consumption in each block for (a) conventional monitoring system without an EC and (b) proposed event-driven monitoring system.

Figure 17. Energy consumption of the proposed event-driven monitoring system as a function of abnormal input occurrence frequency.

As this frequency decreases, the energy consumption in the proposed monitoring system tends to be dominated by the always-on EC block. The difference between the calculated and measured power consumption tends to increase as abnormality occurrence frequency increases, because the switching power is neglected. Figure 18 compares the
lifetime of a 7500 mAh battery in a conventional monitoring system without an EC and in
the proposed event-driven monitoring system.

Figure 18. Lifetime of a 7500 mAh battery in different monitoring systems as a function of abnormality occurrence frequency.

The battery lifetime in the conventional monitoring system without an EC, as shown in Figure 4a, was calculated based on data sheets and obtained as approximately 48 days, regardless of abnormality occurrence frequency. By contrast, the same battery in the proposed event-driven monitoring system lasts a maximum of 8572 days, when the occurrence frequency is low. This means the battery lasts up to 120 times longer than in a conventional system.

The simulation and experimental results for the SNR of the proposed event-driven monitoring system are compared as the input RMS noise level is varied in Figure 19.

Figure 19. SNR of the proposed event-driven monitoring system with varying input RMS noise level.

The experimental SNR is lower than the simulated SNR by up to 1.86 dB because of the additional noise added to the RMS converter and the peak detector in the experiments. Figure 20 shows the frequency response of $v_{PEAK}$ with a pure sine wave as input, excluding the BPF to allow investigation over a wide frequency range. The 3 dB point, at which the output power drops to half, is as high as 21 MHz.
Figure 20. Experimental results of SNR variation with frequency of a sinusoidal input signal.

6. Conclusions

In this paper, a long-lifetime event-driven wireless monitoring system for pole-mounted transformers is proposed as a low-cost battery-powered solution. The proposed monitoring system is designed for detecting an intermittent abnormal signal in a pole-mounted transformer and transmits measurements of physical quantities on an event basis. To increase the lifetime of the battery, the system includes an EC, which reduces energy consumption by minimizing the normal operating time of each block. The proposed event-driven system increased the battery lifetime by up to two orders of magnitude compared to the conventional system. In addition, an RMS converter and peak detector maximize the SNR and reduce the required sampling frequency. The proposed system substantially reduces operation and maintenance costs and enables low-cost diagnosis of components in pole-mounted transformers.

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