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Efficient Sensor-Based Environmental Monitoring for Stored Missiles: Data-Driven Adaptive Sampling for Battery Optimization

Yunhee Choi [1], Hyunwoo Kim [2], Kwangho Yoo [3], Younho Lee [4] and Sojung Kim [5,*]

[1] Neurosense Co., Ltd.; Senior Researcher; yunhee.choi@neurosense.co.kr
[2] Neurosense Co., Ltd.; Researcher; hyunwoo.kim@neurosense.co.kr
[3] Neurosense Co., Ltd.; Director of Research; kwangho.yoo@neurosense.co.kr
[4] LIG Nex1 Co., Ltd.; Principal Researcher; younho.lee2@lignex1.com
[5] LIG Nex1 Co., Ltd.; Senior Researcher; sojung.kim2@lignex1.com
* Correspondence

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Abstract: *The need for condition-based maintenance and sustainability management of military assets has become increasingly important due to reductions in military personnel and budget constraints. In this context, research is actively being conducted using sensors that collect environmental data to determine optimal inspection intervals and identify vulnerabilities early. This study proposes an algorithm to dynamically adjust the sampling interval based on the rate of change in measured physical quantities to reduce sensor battery consumption. Various environmental sensing data, such as temperature, humidity, acceleration, and pressure, were collected from a simulation device that mimicked the storage environment of actual guided missiles. The analysis of the collected data revealed that setting the RSME threshold within 5 improved battery lifespans by 11% compared to the original data, while demonstrating that the temperature RMSE was estimated to improve by about 4.76 in adaptive sampling and 5.44 in uniform sampling. This demonstrates that our approach may improve maintenance efficiency by monitoring military assets more effectively and for extended periods.*

Keywords: CBM; Missile; Smart Sensor; Power Management; Adaptive Sensing Algorithm

1. Introduction

As the need for military personnel reduction and efficient defense resource allocation increases, the demand for condition-based maintenance (CBM) and sustainability management of military assets has become even more critical. CBM is a modern maintenance approach that uses various sensors embedded in weapon systems to monitor the condition in real-time, collecting and analyzing operational history and maintenance data to determine optimal maintenance requirements Figure 1. This method contributes to efficient resource use by performing maintenance only when necessary and maximizing equipment uptime.

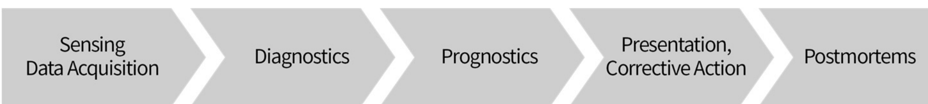


Figure 1. CBM process

Guided missiles are categorized into two types: onboard missiles mounted on platforms and stored missiles kept in ammunition depots. The environmental conditions they are exposed to vary depending on their deployment area. These environmental differences significantly impact the performance and lifespan of the guided missiles. Therefore, research is actively being conducted to create fault prediction models and inspection cycle models based on storage environment information of guided missiles, aiming to determine the optimal inspection cycle and identify vulnerabilities [1-5]. Ultimately, that research aims to enhance the reliability of guided missiles, reduces operational costs, and enables efficient management of logistical assets.

Accurate detection of environmental data is crucial at the initial stages of research. Specifically, it is essential to collect and manage data reliably over extended periods in various environmental conditions where guided missiles are deployed. To achieve this, an IoT sensor module that measures environmental information is required. This module can be installed on missiles in storage or onboard and includes various sensors, signal processing boards, memory, batteries, and communication modules. Given the size and monitoring functionality of the sensor module, achieving a battery lifespan of over 4 years is critical. However, reducing power consumption by extending sensor sampling intervals risks missing crucial environmental changes, which can lead to increased errors in state estimation. Therefore, it is necessary to develop a model that balances sufficient data collection with optimization to ensure reliable operation over the required lifespan.

Accordingly, existing studies have applied techniques such as data reduction, data prediction, and adaptive sampling to save battery lifespan [6]. These methods not only reduce the operational time of the sensors but also help to decrease the server management costs and processing load by minimizing the amount of data uploaded to the central server.

In this paper, a simulation device that mimicked the environment in which guided missiles are stored was implemented and temperature and humidity data was collected. We propose a variation-based adaptive sampling algorithm for temperature data, designed to achieve long-lasting battery operation. The aim of this study is to enhance the efficiency and reliability of intelligent sensor systems while optimizing military asset management.

2. Related Works

There have been various studies focused on reducing power consumption by optimizing data processing in IoT sensor networks. [6-8], which can be broadly categorized into three methods: data reduction techniques that compress data, adaptive sampling techniques that determine minimal sampling needed to extract valid results, and data prediction techniques based on data modeling that utilize the characteristics of the data. Among these, we focused on research applying adaptive sampling to achieve low-power systems in single-sensor operating environments. Below are examples of previous studies that have applied these methods in different fields such as motion detection, medical healthcare, and environment monitoring.

2.1 Reduced Sampling Rate on Physical Activity Monitoring

Reducing battery consumption in wearable devices is crucial. These devices collect accelerometer sensor data to infer user behaviors such as walking, running, eating, cycling, and falling for healthcare purposes. Various research papers have focused on optimizing sampling values for motion sensors to reduce battery consumption while accurately predicting user behaviors. Reference [9] found that, when using accelerometers to estimate behaviors, high-frequency and low-frequency sampling periods yielded similar performance in behavior prediction. Reference [10] compared four different sampling methods—Uniform spacing, Random spacing, Exponential backoff, and Entropy-based sampling— and evaluated their impact on prediction accuracy and battery consumption Figure 2. Reference [11] proposed a method for fall detection by sampling around the initial part of a fall pattern, aiming to reduce battery consumption while still detecting fall patterns. All three studies explored approaches that involve adjusting the sensor's sampling periods to collect meaningful data efficiently.

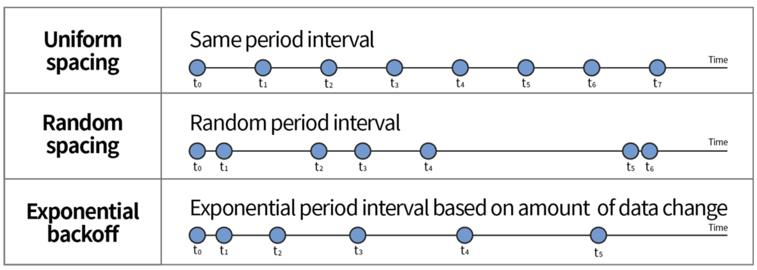


Figure 2. Examples of various sampling methods

2.2 Optimizing sampling rate on ECG HR medical data

In the medical field, higher sampling frequencies are generally required compared to other industries to acquire various bio signals. For instance, electrocardiography (ECG), which measures the heart's electrical signals, typically requires data sampling rates of over 1000 Hz. Reference [12] investigated the use of wrist-mounted optical sensors for photoplethysmography (PPG) data and aimed to enhance its clinical applicability and accuracy. The study determined the minimum amount of data needed for precise health assessments. Using t-tests, Bland-Altman analysis, and regression-based visualization techniques, a sampling frequency of 64 Hz was proposed as an optimal rate for applications requiring high precision in average heart rate (HR) and/or average heart rate variability (HRV). It also demonstrated that a 32 Hz PPG sampling rate could maintain sufficient accuracy while halving data storage requirements. Furthermore, for applications with lower precision requirements, a 21 Hz sampling rate might be appropriate, further reducing data storage needs.

2.3 Optimizing sensor node energy consumption in environment monitoring

Indoor environmental data exhibit periodic characteristics due to temporal redundancy. Reference [13] utilized these characteristics to achieve optimal power consumption by measuring indoor temperature, humidity, and light intensity, and modeling the trends in physical quantity changes to determine appropriate sampling intervals. Gaussian Mixture Models were employed for data prediction, enabling reliable forecasts based on historical data. In this process, the sensor's sampling rate was adjusted according to the reliability of the prediction model. When the predicted values closely matched actual measurements, the sampling rate was reduced to save energy. Conversely, if prediction errors exceeded a certain threshold, the sampling rate was increased to enhance model precision. Additionally, the prediction model was updated periodically with new data to continuously diagnose the appropriate sampling rate in real-time. This low-power modeling approach can also be applied to smart farm systems using various sensors in large-scale farms. Reference [14] monitored temperature and humidity in a large coffee plantation's IoT system, adjusting the sampling rate according to weather changes in the coffee-growing region. This adaptive sampling technique demonstrated a simulation result showing an 11% reduction in power consumption compared to traditional methods.

3. Proposed Method

Guided missiles are composed of two primary categories of shelf-life items: electronic/mechanical components and chemical substances. These missiles are stored either as integrated units within their launch tubes or as disassembled major components in dedicated storage containers. In the case of tube-launched guided missiles, the launch tubes are engineered to allow for the easy replacement of desiccants, ensuring that the internal humidity is maintained below a specific threshold. Additionally, each component is sealed during assembly with rubber O-rings at the joints to prevent moisture ingress. Both tube-launched and container-stored guided missiles are kept in magazines that either operate temperature-controlled dehumidification systems or are maintained under ambient conditions [15].

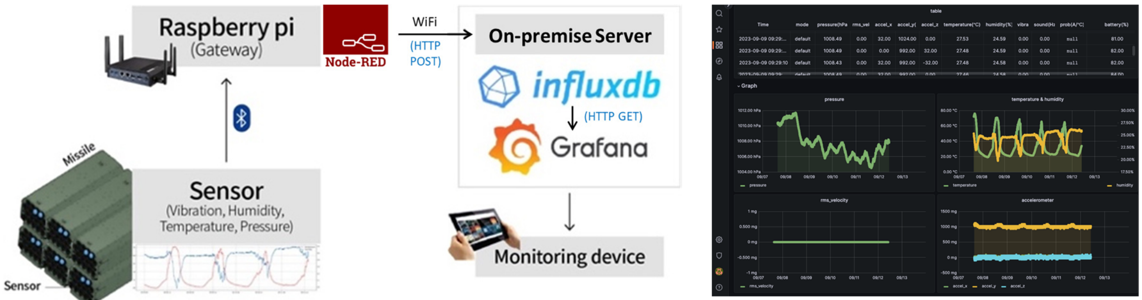
Since the storage lifespan of a guided missile constitutes nearly all (99.9%) of its total lifespan [4], an environmental monitoring system was developed to simulate and analyze environmental conditions in missile storage. Based on the analysis of the measured data, a variation-based adaptive sampling algorithm is proposed. The performance of the applied algorithm was evaluated.

3.1 The Environment Monitoring System for Simulated Guided Missile Canister

The setup of environment monitoring system, system architecture, and data display are shown below. As shown in Figure 3, a storage launch container was designed to simulate the storage environment of an individual guided missile canister. Inside this sealed container, a dehumidifier was installed to maintain stable humidity levels, and IoT sensors were placed to monitor various environmental variables. In addition, identical sensors were installed outside the mock launch container to compare and analyze the internal and external environments, allowing for simultaneous measurement of environmental data.

(a) (b) (c)

Figure 3. Environment monitoring system for simulated guided missile canister: **(a)** Installation of dehumidifiers and IoT environmental sensor modules inside the storage canister **(b)** Exterior of the canister **(c)** Simulated canister device and reference sensors installed on the outer wall of the window



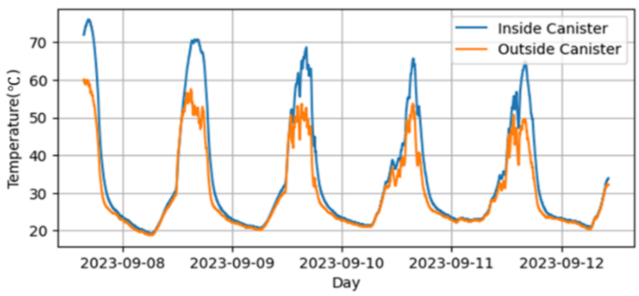
(a) (b)

Figure 4. Architecture and data of the proposed environment monitoring system: **(a)** Overall system architecture **(b)** Data visualized results in Grafana program

Figure 4 illustrates the overall system architecture for processing the measurement data. The collected data were transmitted to a server via Bluetooth communication through a gateway developed with a Raspberry Pi single-board computer. The gateway, running Node-RED, facilitated real-time data acquisition, processing, and transmission. It processed sensor data before forwarding it to an on-premise server via Wi-Fi communication using HTTP POST requests. The received data were stored in an InfluxDB time-series database, enabling structured data management optimized for time-dependent sensor data. Grafana tools then retrieved the stored data using HTTP GET requests to generate real-time visualizations. This architecture enables continuous monitoring and analysis of the simulated guided missile canister's condition through an intuitive, data-driven interface.

3.2 Analysis of gathered data

As shown in Figure 5, the environmental data of the temperature and humidity have variation patterns over a 5-day period.



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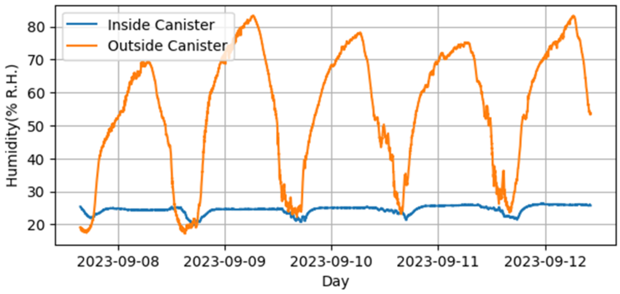


(b)

Figure 5. Collected 5-day environmental data of inside and outside of the canister. Both data were measured in every 30 seconds: **(a)** Temperature; **(b)** Humidity

When comparing the internal and external conditions, a temperature difference of up to 15°C and a humidity difference of 57% were recorded. Notably, inside the launch container, temperature fluctuations of up to 22°C per hour and humidity variations of 2.8% were observed. Additionally, the square-wave pattern of humidity changes due to the dehumidifier operation was distinctly visible.

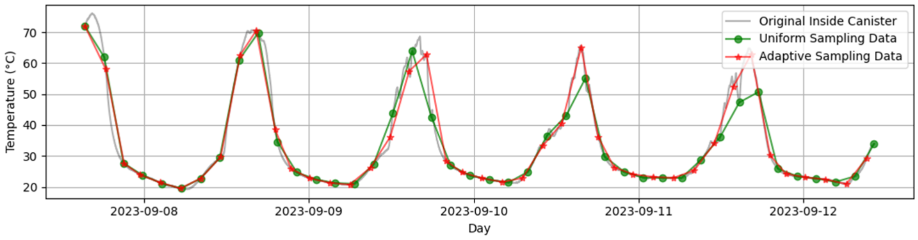
3.3 Applied Algorithms and Data Processing

Based on the analysis of several prior studies, we explored variable algorithms that can be implemented in a lightweight manner at the sensor level, referring to reference [16]. This paper proposed an algorithm that dynamically adjusted the next sampling period based on the changes in the measured physical quantities. The algorithm was designed to be applied in real-time, with shorter sampling periods occurring as the magnitude of data changes increased. Equation (1) represents the variable algorithm proposed by reference [16], while the time between measurements (TBM) was determined by E which is the initial sampling rate in the normal case and S which is a tuning constant that determines the sensitivity of the changes. y_{ti} and y_{ti-1} denote the current and previous sensor values, respectively and M_{ti} and M_{ti-1} are the current and previous time of measurements, respectively. The next measurement M_{ti+1} could be defined as described in Equation (1). Equation (2) describes the new variable algorithm proposed in this study especially for the periodic cycle data. By incorporating the rate of change as a divisor, the algorithm effectively adjusts the sampling period E based on the variability of the observed data. When the rate of change is high, the denominator increases, resulting in a shortened sampling interval. Conversely, when the rate of change is low, the denominator decreases, leading to a longer sampling interval. In Equation (2) TPeak denotes the period of the data while E and S retain the same meanings as previously defined.

$$M_{ti+1} = M_{ti} + \ TBM, \qquad TBM = E - \left(S \times \left|\frac{(y_{ti}-y_{ti-1})}{(M_{ti}-M_{ti-1})}\right|\right), (i \in 1,2,3, \cdots n) \tag{1}$$

$$M_{ti+1} = M_{ti} + \ TBM, \qquad TBM = \frac{T_{peak}}{E + S \times \left|\frac{(y_{ti}-y_{ti-1})}{(M_{ti}-M_{ti-1})}\right|} \ , \quad (i \in 1,2,3, \dots n \ , \ E \geq 2) \tag{2}$$

Most environmental variables do not exhibit strict linear trends but rather follow nonlinear patterns characterized by periods of rapid increases and decreases, as well as gradual fluctuations. The adaptive sampling approach in Equation (2) is designed to better capture such nonlinear variations by dynamically adjusting the sampling rate in response to changes in data trends. This approach improves upon the limitations of Equation (1), where high variability led to an excessively rapid reduction in the sampling interval, while low variability resulted in little to no adjustment. According to the Nyquist-Shannon sampling theorem, a signal must be sampled at least twice the frequency of its highest significant frequency component to ensure accurate reconstruction without information loss. In other words, identifying the primary cycle of temperature variations and setting the sampling interval to be less than or equal to half of that cycle (e.g., E ≥2) is essential for maintaining data integrity and minimizing potential loss of critical information. Figure 6 visualizes how the actual data point acquisition intervals change and how sampling is performed according to equation (2).



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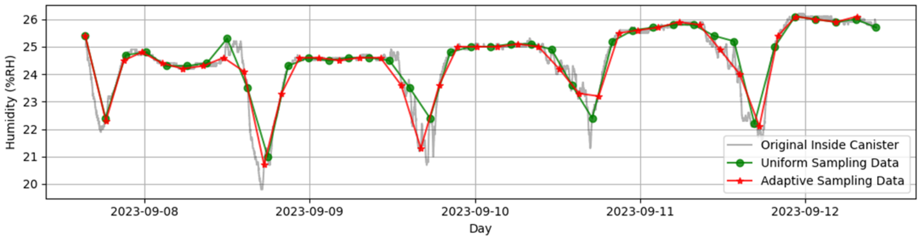


(b)

Figure 6. An example of the applied algorithm showing the intervals between sampling points (red dots): **(a)** Temperature data; **(b)** Humidity data

In this study, the effectiveness of the variable algorithm was evaluated using simulated temperature and humidity data collected from a guided missile launcher. It was observed that patterns of large increases and decreases, as well as small increases and decreases, repeated every 24 hours. Therefore, this study applied TPeak to 24 for environmental data with a 24-hour periodic cycle and adjusted E to 24, 12, 8, and 4. As TPeak is devided by E, this configuration results in initial sampling intervals to 1 hour, 2 hours, 3 hours, and 6 hours, to test the algorithm's performance respectively. For each initial sampling period E, slope S was varied from 0 to 2, and the degree of estimation of temperature and humidity changes was explored. To compare the performance with fixed interval sampling techniques, the sampled data for each S value was linearly interpolated, and the RMSE(Root Mean Square Error) and MAE(Mean Absolute Error) metrics were used to compare it against the original data. The interpolation error was quantitatively analyzed to assess the impact of sampling period adjustments.

Additionally, to directly evaluate the effectiveness of the proposed variable sampling algorithm, battery lifespan was estimated in a simulated environment using virtual temperature and humidity IoT sensors. The battery lifespan was approximated by calculating the current consumption required for sensor operation and wireless communication based on the number of sampling instances. Equation (3) presents a simplified model for daily power consumption, where $P_{sampling}$ represents the energy consumption per sampling operation (mAh), and $P_{transmission}$ denotes the energy consumption per data transmission (mAh). $N_{samples}$ corresponds to the number of sampling events per day, while $N_{transmissions}$ indicates the number of data transmissions per day. The estimated battery life (in days) is then determined using Equation (4), where $C_{battery}$ represents the total battery capacity (mAh). This equation provides an estimate of the sensor system's operational duration based on its daily energy consumption.

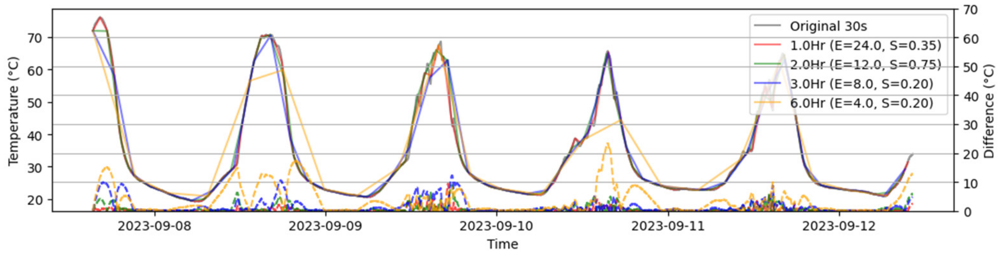
$$E_{daily} = P_{sampling} \times N_{samples} + P_{transmission} \times N_{transmissions} \tag{3}$$

$$L_{estimated} = \frac{C_{battery}}{2 \times E_{daily}} \tag{4}$$

This analysis aims to assess the efficiency of the variable sampling algorithm under real-world conditions and quantify its impact on extending battery lifespan compared to fixed sampling methods. However, the actual battery lifespan may vary depending on the specific sensor design and operational scenarios. Furthermore, considering the effects of environmental conditions on battery performance, a conservative degradation model was adopted to ensure realistic lifespan predictions. Zheng et al. [17] reported that lithium-ion batteries can experience up to a 50% reduction in performance under low-temperature conditions, while Leng et al. [18] identified temperature as a key factor accelerating battery degradation. Based on these findings, a 50% performance reduction was incorporated into the battery lifespan estimation model.

4. Experimental Evaluation

Figure 7 visualizes the results of sampling performed at each initial time interval and the corresponding error rates. The figure illustrates how the error rates vary with different initial sampling periods, providing a clear comparison of the performance of the variable sampling algorithm against fixed sampling intervals.



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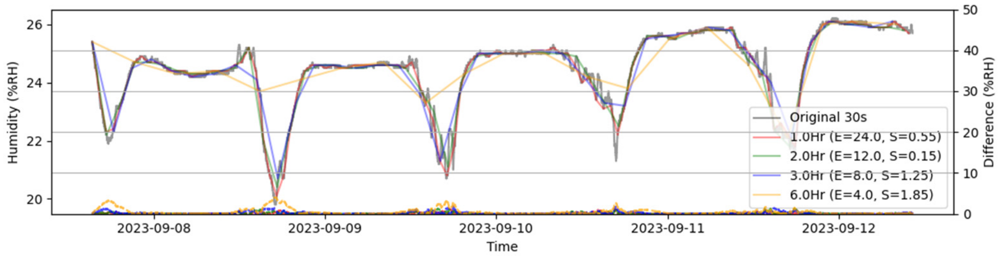

(b)

Figure 7. Estimation of temperature data and error rate when adaptive sampling starting at 1, 2, 3, 6 hours intervals was applied: **(a)** Temperature data; **(b)** Humidity data

Table 1 shows both the prediction error and estimated battery lifespan between uniform sampling and variation-based adaptive sampling algorithm. Within the same number of samples and battery life, it was observed that adaptive sampling generally exhibited lower prediction performance metrics compared to uniform sampling. Compared to the 1Hr interval data with a 6Hr interval, battery lifespan improved by 11%, while demonstrating the temperature RMSE was estimated to improve by about 4.76 in adaptive sampling and 5.44 in uniform sampling. Additionally, as the initial sampling period increased, the improvement in prediction performance metrics with the adaptive sampling method also increased. With an initial sampling period of 1 hour, the RMSE was estimated to improve by about 0.23. However, increasing the period to 6 hours resulted in an estimated improvement of around 0.91. This suggests that longer sampling intervals allow adaptive sampling to capture more meaningful data compared to fixed interval methods.

Table 1. Performance metrics of temperature and humidity data and battery lifespan estimation when fixed interval uniform sampling and variable interval adaptive sampling methods are applied

Initial Sampling Period	Estimated Battery Lifespan (Years)	Uniform sampling				Adaptive sampling			
		Temperature		Humidity		Temperature		Humidity	
		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
1Hr	5.02	1.12	0.47	0.22	0.11	0.89	0.40	0.19	0.10
2Hr	5.31	1.80	0.91	0.29	0.16	1.44	0.73	0.25	0.14
3Hr	5.48	3.62	1.91	0.43	0.23	2.74	1.46	0.37	0.21
6Hr	5.61	6.56	4.25	0.90	0.52	5.65	3.51	0.88	0.50

Meanwhile, the impact of the variable algorithm on humidity data was less significant compared to temperature data. This is because the adaptive sampling algorithm was designed based on temperature data, and the actual variability in humidity data was limited by the influence of the dehumidifier.

In this study, an adaptive sampling algorithm was proposed to save battery consumption for environmental sensors using CBM processes. The algorithm was applied to simulated data collected in practice and compared with fixed sampling methods. The comparison results showed that the improvement effect of this algorithm was somewhat less than that achieved using prediction models proposed in previous research [5]. This discrepancy is attributed to the algorithm's limitation of relying on a simpler arithmetic estimation approach through linear slope change calculations, as opposed to complex model-based change estimation.

5. Conclusions and Future Research

Intelligent sensors have become a key technology that goes beyond simple data collection to analyze data and deliver meaningful information to users [7]. The algorithm used in this study is a crucial component for implementing such intelligent sensors, designed very efficiently through lightweight arithmetic operations. This design allows it to be effectively operated on low-power IoT sensors like Cortex-M series, and particularly through variable sampling algorithms, it can self-determine the sampling period based on physical quantities, maximizing energy efficiency while collecting highly accurate data.

Based on this research, we aim to utilize the algorithm for more accurate predictive models in guided missile failure prediction and inspection cycle models by operating IoT sensors efficiently. This approach is expected to enhance the overall reliability and operational efficiency of CBM systems. The adaptive sampling method proposed in this study is not restricted to a specific guided missile system but can be extended to various missile types requiring environmental monitoring during long-term storage. Moreover, it can be applied to state-based maintenance systems in various military, industrial, and commercial applications. It is anticipated that the algorithm will play a significant role in extending the lifespan of sensor networks, reducing maintenance costs, and minimizing system downtime.

Future research will focus on expanding the application range of the proposed algorithm and validating its effectiveness through empirical studies in real-world environments. Additionally, efforts will be directed towards developing intelligent sensors with active operational state recognition by applying AI-based modeling techniques.

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