Sensing the Unknowns: A Study on Data-Driven Sensor Fault Modeling and Assessing its Impact on Fault Detection for Enhanced IoT Reliability

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***Abstract*—In the context of the Internet of Things (IoT), the effective operation of IoT applications heavily relies on the functionality of sensors. These sensors are prone to failures or malfunctions due to various factors, including adverse environmental conditions and aging components within sensors. To mitigate the impact of faulty sensors on system performance, notable research has focused on employing machine-learning techniques to detect faulty sensor data. In this context, due to the scarcity of real faulty data records and challenges in generating them even in controlled environments, researchers often model faulty data to create synthetic datasets containing normal and abnormal data for evaluating fault detection models. Our empirical investigation reveals that the current modeling approach to simulate faulty sensor scenarios does not adequately mirror the complexity of real-world faulty sensor behaviors. Therefore, to improve the efficacy of fault detection algorithms in practical applications, it is imperative to investigate sensor fault models further. To address this gap, we conducted a comparative analysis of existing fault models and proposed a novel composite approach for modeling faulty sensor behaviors that can more effectively capture real-world sensor behaviors. Our focus was to evaluate how different fault models impact the effectiveness of anomaly detection algorithms when tested in real-world scenarios. The evaluation included algorithms trained on synthetic datasets derived from various fault models, assessing their performance in identifying real-world faulty data. We also provide diverse labeled datasets, including normal and abnormal data collected from real-world applications.**

***Index Terms*—Fault Modeling, IoT, Sensors, Reliability**

I. INTRODUCTION

In recent years, a growing focus has been on incorporating the Internet of Things (IoT) into various systems. This is due to the ability of smart things (e.g., sensors, cameras, etc.) to gather valuable data about system operations, empowering us to make more informed decisions toward more efficient systems. Nevertheless, with the increasing reliability of these systems, sensors have garnered a reputation for being the ”weak link.” The system’s performance could suffer and potentially lead to a complete system breakdown due to any sensor malfunction [1]. Hence, to minimize the consequences of abnormal events, it is essential to have a good insight into how sensors fail and behave to detect them promptly [2].

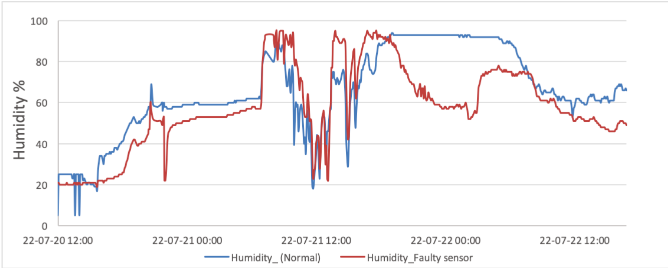

Fig. 1: Illustration of a faulty humidity sensor behavior when sensing material is degraded over time.

While extensive research has addressed fault detection and diagnosis in various IoT applications, there is a notable lack of endeavors specifically centered on formulating realistic fault models and systematically categorizing sensor faults [3], [4]. This gap primarily arises from the difficulty or impracticality of gathering adequately large and diverse real faulty data. Consequently, developing an accurate model for detecting anomalies can be notably affected by these limitations.

In this context, due to the limited availability of data from real faulty sensors, current literature on classification-based fault detection simulates and injects faulty data into their datasets, assuming that a fault may fall into one of the following categories: bias, drift, noise, gain, outliers, or being stuck [5]–[7]. Characterizing sensor responses under fault conditions can be simplified by simulating a single fault at a time, such as a bias, to reproduce faulty sensor behavior. This has benefits for theoretical modeling. When using these models in real-world situations, it’s important to be aware of their limits. Although these models perform well in controlled or theoretical environments, they might not be able to handle the complexities and variances found in real-world applications. For instance, Figure 1 illustrates a case from our dataset, where humidity data collected by a degraded old sensor exhibits intricate behavior that cannot be accurately represented by a single fault, like bias or drift. These observations highlight the need for further study in relation to modeling the behavior of faulty sensors so that it can be used to identify sensor behavior

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in real-world applications more effectively.

Our research focuses on overcoming the limitations of current fault modeling techniques to achieve more realistic representations of faulty sensor behavior. These fault models play a crucial role in generating synthetic datasets for establishing fault detection models. Following a thorough assessment of existing fault models, we describe a novel composite technique for modeling faulty data that treats faulty data as a multi-cause phenomenon, resulting in a more accurate capturing of real-world sensor behavior. Our assessment is centered on comprehending how these fault models, including our proposed one, affect anomaly detection algorithms' performance in practical settings. We assess the algorithms trained on synthetic data derived from various fault models, emphasizing their effectiveness in identifying real-world faulty data. Our proposed approach allows us to avoid biases in evaluating fault detection performance established in controlled environments and strives to emulate real-world conditions as closely as possible. This experimental validation highlights the value of our approach in real-world applications where the possibility of gathering real faulty data is challenging, impractical, or costly. The rest of the paper is structured as follows. We present our use case and the rationale behind the research in Section II. Sensor fault modeling is covered in detail in Section III, which also establishes the foundation for the analysis of fault modes and the subsequent introduction of a new fault model. The methodology and experimental results for evaluating the efficacy of our approach in enhancing fault detection model performance are delineated in Sections IV and V. Lastly, in Section VI, we outline the future work.

II. Use case scenario and Problem Statement

Without loss of generality, this investigation focuses on an air monitoring system that measures temperature, humidity, and CO2 levels. The consequences of irregular system operation can include increased energy consumption, lowered air quality, and decreased productivity. We have selected this use case for several reasons: the application is well known and understood; the employed sensors are very broadly used also for other applications; and the sensors are diverse enough to exhibit different behaviors when failing or degrading.

To address the complexities arising from potential faults and refine our understanding for more precise sensor fault modeling, we delve into the fundamental operating principles of these sensors and gain insight into prevalent fault mechanisms. In the following subsection II-A, we will go over this issue in-depth and provide a thorough understanding of sensor properties. The existing restriction in modeling the behavior of the sensor is then explained in subsection II-B.

A. Sensing Process Characterization

Sensors are designed to measure various phenomena by leveraging specific physical properties or behaviors of materials. With the appropriate setup, these properties can be utilized to sense different factors. For example, resistance can be employed to measure values like temperature, strain, force, light intensity, or gas concentrations, depending on the specific application. This illustrates how sensors are versatile tools capable of capturing a wide array of data. However, the effectiveness of these sensors in delivering precise and reliable measurements is significantly shaped by their distinct physical designs. These designs, in turn, influence the type and frequency of sensor faults that may arise. The current research discusses sensor mechanisms corresponding to three different sensors mostly used in air monitoring systems, as follows:

1) Non-dispersive infrared sensor (NDIR): Co2 sensor
2) Polymer-based capacitive sensor: humidity sensor
3) Negative Temperature Coefficient(NTC) thermistor: temperature sensor

The list is undoubtedly not comprehensive, but it represents the multiple commonly used sensors in air monitoring applications. It is essential to mention that this research explicitly addresses errors arising from the failure of the sensing mechanism itself and doesn't investigate other factors like circuitry or software responsible for sensor output processing.

1) Non-dispersive infrared sensor (NDIR): The mid-infrared (mid-IR) spectral range (wavelength $\lambda \sim 2$ to 20 μm) is often referred to as the 'molecular fingerprint' region, characterized by distinct vibrational and rotational patterns in gas molecules. NDIR spectroscopy, a mid-IR gas sensor, employs an *Infrared Light Source*, typically an infrared LED or lamp, emitting light at a specific wavelength corresponding to the gas's absorption band [8]. Within the NDIR sensor, an *Optical Gas detection Chamber* allows infrared light to pass through ambient air. As the light interacts with CO2 molecules, the *Infrared Detector* component of the sensor quantifies the amount of absorbed light, providing a direct measurement of CO2 concentration. The accuracy of the NDIR sensor depends on the intensity of the *Infrared Light Source*, the *Optical Gas detection Chamber*, and the *Infrared Detector* configuration. The common NDIR sensor faults include:

1) Degradation, deterioration, or complete failure of the infrared light source leading to bias, gain, drift, and stuck faults. In this situation, the decreased emission intensity of the infrared light causes the accurate measurement of gas concentration to be affected [9].
2) Spectral Shift in the infrared light source spectral characteristics due to the temperature fluctuation or high temperature resulting in bias and drift [10].
3) Contamination of the optical components or gas detection chamber can affect the sensor's sensitivity and lead to bias or drift in its readings.
4) Thermal Expansion of the gas detection chamber due to the high temperature affects the interaction of IR light with the CO2 molecules and leads to bias and gain.
5) Water vapor interference occurs when the presence of water vapor in the gas sample affects the sensitivity of the gas concentration and can lead to bias [9].
6) Interference from multiple gases in the sample can cause inaccurate readings, resulting in bias or noise [11].

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2) Polymer-based capacitive humidity sensor: A capacitive humidity sensor employs a humidity-sensitive capacitor to measure relative humidity. These sensors utilize a humidity-sensing layer, which can be made of various materials like electrolytes, ceramics, or polymers. In this study, we specifically address polymer-based sensing layers. The sensor operates on the principle that changes in the dielectric properties of this humidity-sensitive layer lead to variations in the sensor's capacitance. These capacitance changes are then used to measure relative humidity in the surrounding environment.

1) Exposure to chemicals or contamination with dust, oils, or other particles can lead to the intrusion of external substances into the polymer, occupying the spaces normally captured by water. It leads to the degradation of the polymer film's ability to amplify the number of water molecules, especially in high and low-humidity situations. In this regard, bias, drift, and stuck can happen [12].
2) Aging or degradation of polymer materials, either through prolonged use or exposure to high temperatures, can result in problems like gain, bias, and drift [13].
3) Extreme low humidity can lead to a decrease in the sensor's capacitance sensitivity. The dielectric properties of the polymer material between the sensor's plates may change less significantly, resulting in reduced capacitance changes and less sensitivity [14].

3) NTC thermistor: temperature sensor: An NTC thermistor is a temperature sensor with nonlinear resistance-temperature characteristics. Its resistance decreases as temperature rises due to its negative temperature coefficient. This nonlinearity can make converting resistance measurements into accurate temperature values more challenging because the resistance-temperature relationship follows an exponential curve. The common faults that can happen are:

1) The thermistor's resistance decreases as temperatures increase, leading to higher power consumption. Raised power levels, in turn, trigger self-heating within the thermistor, a consequence of the heat generated by the flowing current. This self-heating can introduce measurement inaccuracies, leading to bias or drift, especially in scenarios when the temperature changes quickly [15].
2) Prolonged exposure to high temperatures or repeatedly subjecting the thermistor to temperature fluctuations can cause a thermistor's resistance to change from its initial value, leading to drift [16].

B. Summary and problem statement

In this section, we have explored diverse sensor technologies, including NDIR, capacitive, and thermistor, while addressing potential fault scenarios for each. These scenarios encompass a spectrum of failures, including bias, drift, outliers, and other deviations, which can be traced back to factors such as contamination, aging, and various environmental and operational variables. Notably, it can be seen that a single factor, like contamination or aging, can lead to different types of faults that may occur simultaneously, contributing to the complex behavior of faulty data [17]–[19]. However, the scarcity of real-world faulty data records has limited the insight into modeling faults, especially where multiple fault types may coexist, resulting in complex sensor behaviors. This crucial point is often neglected in existing research, where fault detection models are built using simulated faulty data and subsequently tested on controlled simulated datasets, overlooking the complexities inherent in real-world sensor behaviors. Hence, in the next section, we investigate the modeling of sensor behavior and then propose our approach to model faulty data, which can more effectively capture real-world sensor behavior compared to established ones.

III. Sensor Fault Classification and Proposed Fault Modeling Approach

In the context of modeling sensor data, the data originating from a sensor is denoted as $s(n, i, f^{\mathrm{n}}{}_{\mathrm{i}})$. Here, n represents the node id, i corresponds to the index of measurements, and $f^{\mathrm{n}}{}_{\mathrm{i}}$ captures the *ith* measurement by node n. The $f^{\mathrm{n}}{}_{\mathrm{i}}$ can be represented by a linear regression model denoted in Eq.1 [6]:

$$f^{\mathrm{n}}{}_{\mathrm{i}} = \beta + \alpha . x^{\mathrm{n}}{}_{\mathrm{i}} + \eta \tag{1}$$

where β is a constant offset termed Bias, α represents a multiplicative factor called Gain, where the waveform remains unchanged [3], $x^{\mathrm{n}}{}_{\mathrm{i}}$ denotes a faultless i*th* sensor reading, and η is a random variable denoted as Noise. *Dunia et al.* [6] demonstrated that the noise can be effectively captured as Gaussian white noise, as outlined in Eq. 2. This exhibits a probabilistic distribution with a mean of zero and a variance of non-faulty data denoted as δ^2.

$$\eta \sim \mathcal{N}(0, \delta^2) \tag{2}$$

A. Current sensor fault modelling approaches in Anomaly Detection context

The state-of-the-art study in the fault detection domain shows that modeling faults in time-series data is widely applicable, offering a structured approach for simulating fault scenarios and then assessing their anomaly detection algorithms' performance [3]–[7]. To the best of our knowledge, current studies usually defined six different faults based on Eq. 1, namely drift, spike, bias, precision degradation, gain, and stuck. Table I provides an overview of all addressed faults, along with their definitions, established calculation formulas, and potential causes. In sensor output, bias introduces a constant offset (β). Precision degradation, characterized by noise (η) with zero mean and high variance, reduces measurement precision. Gain fault involves a scaling factor (α) applied to sensor measurements. Drift occurs when sensor data is gradually influenced by a linearly increasing bias (β). A stuck fault keeps the sensor output constant, whereas a spike represents an abrupt departure in data. Several studies [3], [4] model bias, drift, and gain by including Gaussian noise (η) to provide fluctuations when modeling these faults.

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TABLE I: Overview of the sensor faults, their definitions and causes

Fault type	Definition	Cause	Literature
Bias	Shifting readings higher or lower by a fixed offset: $$f^{\mathrm{n}}{}_{\mathrm{i}} = \beta + x^{\mathrm{n}}{}_{\mathrm{i}} \quad (3)$$	Degradation of sensing material, Calibration issues, Environmental factors such as high temperature, Sensor-to-Surface interface issues, change the magnetic properties	[3], [12], [20]–[22]
Precision degradation	The variance and covariance of the measured data exhibit deviations beyond their typical range, resulting in heightened variability within the measurements: $$f^{\mathrm{n}}{}_{\mathrm{i}} = x^{\mathrm{n}}{}_{\mathrm{i}} + \eta,\ \eta \sim \mathcal{N}(0, \delta^2) \quad (4)$$	Electronic interference, Degradation (aging effect), Environmental factors, Vibrations and shock	[3], [21], [23]
Gain	The readings are transformed by amplification or improper scaling factor, where the waveform itself does not change: $$f^{\mathrm{n}}{}_{\mathrm{i}} = \alpha . x^{\mathrm{n}}{}_{\mathrm{i}} \quad (5)$$	Sensor-to-Surface interface issues, Wiring problems, Environmental factors causing sensing material deterioration and degradation, Electronic interference	[3], [20]–[22]
Drift	Measurements gradually change over time, even with constant conditions. Non-faulty data is affected by a linearly increasing bias, added incrementally to each data point based on its position in the sequence: $$f^{\mathrm{n}}{}_{\mathrm{i}} = \beta(\frac{i-j}{T_{\mathrm{R}}}) + x^{\mathrm{n}}{}_{\mathrm{i}}, \quad (6)$$ T_{R}=Duration of the ramp, j=Fault starting position	Degradation of sensing material, Wiring issues, Vibration and shock, Environmental factors (e.g. high temperature, chemical exposure), Calibration issues	[12], [18], [22]–[25]
Stuck	The measurements remains persistently fixed at a constant value, such as zero/null or at a specific level, indicating a lack of response to changing conditions: $$f^{\mathrm{n}}{}_{\mathrm{i}} = \beta \quad (7)$$	Power supply failure, Disconnection of wires, Strong magnetic fields, Connection problems, Environmental factors (e.g. extreme weather condition, harsh external activities)	[1], [3], [7], [21]
Spike	Intermittent high-amplitude deviations that disrupt normal readings, appearing unpredictably	Voltage variation, Environmental factors, Unstable electrical contact	[3], [7], [26]

While focusing on simulating individual fault modes, such as bias, in a controlled environment can enhance our understanding of these specific faults and aid in the development of anomaly detection models, it is essential to recognize the complexities inherent in real-world sensor scenarios.

B. Proposed fault modeling approach

Unlike controlled simulations for producing synthetic sensor data, real-world sensor measurements might be characterized by noise, irregularities, and multiple fault modes occurring simultaneously, posing significant challenges for fault detection. Our empirical data collected from various faulty sensors supports the observation that a complex characteristic, such as faulty sensor behavior in real-world applications, can be a multi-causal phenomenon. Therefore, it is crucial to strike a balance between controlled simulations and real-world data to develop robust and effective fault detection models. Unfortunately, although considering the combination of multiple fault factors in modeling faulty sensor scenarios is straightforward, till now, literature has not considered this approach for modeling the faulty scenario. Based on our examination of real-world data and our understanding of potential threats to sensor failure, including their impacts like contamination leading to diverse fault modes (as detailed in Section II)), we strongly recommend incorporating all three factors—noise (η), bias (β), and scaling (α)—when modeling faulty data. This inclusive approach aims to enhance the simulation of sensor behavior by accounting for the distinct effects each fault factor has on sensor data. By taking into account all three factors, our approach can provide a better answer for the complex nature of faulty data in the real world than using only one factor, such as bias, in modeling faulty data.

IV. Methodology and Evaluation Procedure

Our methodology follows a well-structured series of steps in our pursuit to model the faulty sensor behaviors that provide the possibility to produce a synthetic dataset that effectively captures the intricacies of sensor behavior in real-world applications. Firstly, we collect data from various sensors, including normal and abnormal readings, providing a required reference for comparative analysis. Subsequently, guided by Eq. 1 for simulating synthetic faulty data, we create a range of datasets that exhibit different types of failures, including our proposed one. Finally, we proceed with training the anomaly detection model and its subsequent evaluation using real-world data, including normal and abnormal samples in section V.

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A. Data collection from real-world IoT applications

This work conducts several experiments to prepare four datasets containing sensor data from real-world implementations, encompassing both healthy and faulty sensor readings. The initial experiment utilized three $SCD30$ carbon dioxide measurement sensors employing NDIR technology. These sensors began in a normal operational state, and their measurements were compared to those obtained from a reference device. Subsequently, one of the sensors was subjected to elevated temperatures to accelerate the degradation of its sensing material and potentially deform the optical chamber, both known factors associated with sensor faults under extreme stress conditions [10]. Data were recorded at 12-minute intervals over ten days. The datasets were labeled according to the $SCD30$ datasheet with an accuracy of +/-50 ppm.

The second experiment involved two $DHT11$ sensors, utilizing thermistor technology for temperature measurement and polymer-based capacitive technology for humidity measurement. One of these sensors had experienced aging, leading to performance degradation over time [18], while the other was a new unit verified against a reference device. Data from both sensors were collected over a week every 10 minutes. The datasets were labeled based on the $DHT11$ datasheet, which specifies an accuracy of ±2 for temperature and ±5% for humidity measurements. The third experiment commenced with both $DHT11$ sensors operating in a healthy state. However, over a period of four days, one of the sensors became contaminated due to the infiltration of foreign particles, leading to the accumulation of soil and debris on its surface.

In the fourth experiment, three $DHT11$ sensors were employed. Initially, two sensors were in a normal operational state and underwent calibration against a reference device, while the third sensor had experienced aging due to prolonged use. Subsequently, one of the healthy sensors was exposed to high-temperature conditions, resulting in an alteration of its operational characteristics and the generation of faulty data for both temperature and humidity measurements. The data was collected over a one-month period at 10-minute intervals and labeled based on a $DHT11$ datasheet.

The obtained faulty data exhibited complex behavior in all four experiments, revealing the inadequacy of modeling faults with a single fault factor. As a result, a thorough understanding of sensor faults is required, given the possibility that a hazard, such as degradation, may produce multiple faults concurrently.

B. Synthetic dataset generation

In our study, we systematically generated synthetic datasets, incorporating various types of sensor errors using Eq. 1. These datasets were derived from normal data collected during experiments outlined in subsection IV-A, with simulated errors injected. The errors include bias, precision degradation, gain, and drift, obtained from equations 3, 4, 5, 6, and our proposed model, encompassing all three error factors—noise, bias, and gain. Furthermore, we have examined diverse combinations of fault factors to conduct a comprehensive comparative analysis, including integrating gain and bias, combining drift and noise, considering gain and noise, and simultaneously incorporating bias and noise factors.

C. Preparing the training and test sets

To assess the effectiveness of our fault modeling approach, we generate multiple training sets incorporating diverse fault types to evaluate their ability to replicate real-world faulty data behavior. To generate synthetic training datasets for CO2, temperature, and humidity, we followed the methodology outlined in subsection IV-B, resulting in nine distinct synthetic training sets for each of them. We ensured that each synthetic training dataset had a balanced distribution of normal and abnormal data points to help the model learn from both classes equally. We generated several training sets for each fault type by changing its fault factors, like varying bias values, to evaluate the dataset's efficacy in capturing the sensor behavior in real-world applications. Also, we provided a training set using real data to have a basis for comparison. For each sensor, all training sets are of uniform size, sharing the same normal data while varying only in terms of abnormal data. This approach ensures facilitating fair comparisons and evaluations. Figure 2 displays a subset of our training sets, representing a selection of the humidity, temperature, and CO2 data. The test datasets for CO2 and temperature incorporate real sensor readings obtained during the first and second experiments, while for Humidity, two distinct test sets are derived from the third and fourth experiments, each portraying unique fault scenarios (i.e., contamination with an external factor and degradation). To mitigate over-fitting risk, we ensure a balanced distribution of normal and abnormal data points in all test sets.

D. fault detection model

In this demonstration, we utilize our previously developed anomaly detection model, outlined in [19], to illustrate the influence of various fault modeling approaches on the effectiveness of fault detection algorithms. We used two classifiers in our anomaly detection model, specifically the Support Vector Classifier (SVC) and Convolutional Neural Network (CNN), to evaluate their performance in classifying the given data. The CNN model consists of three convolutional layers with batch normalization and ReLU activation, followed by a max pooling layer, a global average pooling layer, and a dense output layer with softmax activation.

V. Comparative Analysis and Discussion

In this section, we conduct a detailed comparison of different fault models to assess their ability to replicate real sensor behavior when used to establish fault detection methods. The evaluation relies on datasets and fault detection models discussed earlier in section IV. Also, to provide a basis for analysis, we train fault detection models with real normal and abnormal data to have a better insight into the performance of synthetic data in establishing fault detection models. For the sake of clarity, the performance evaluation metrics, originally elaborated in our prior publication [19],

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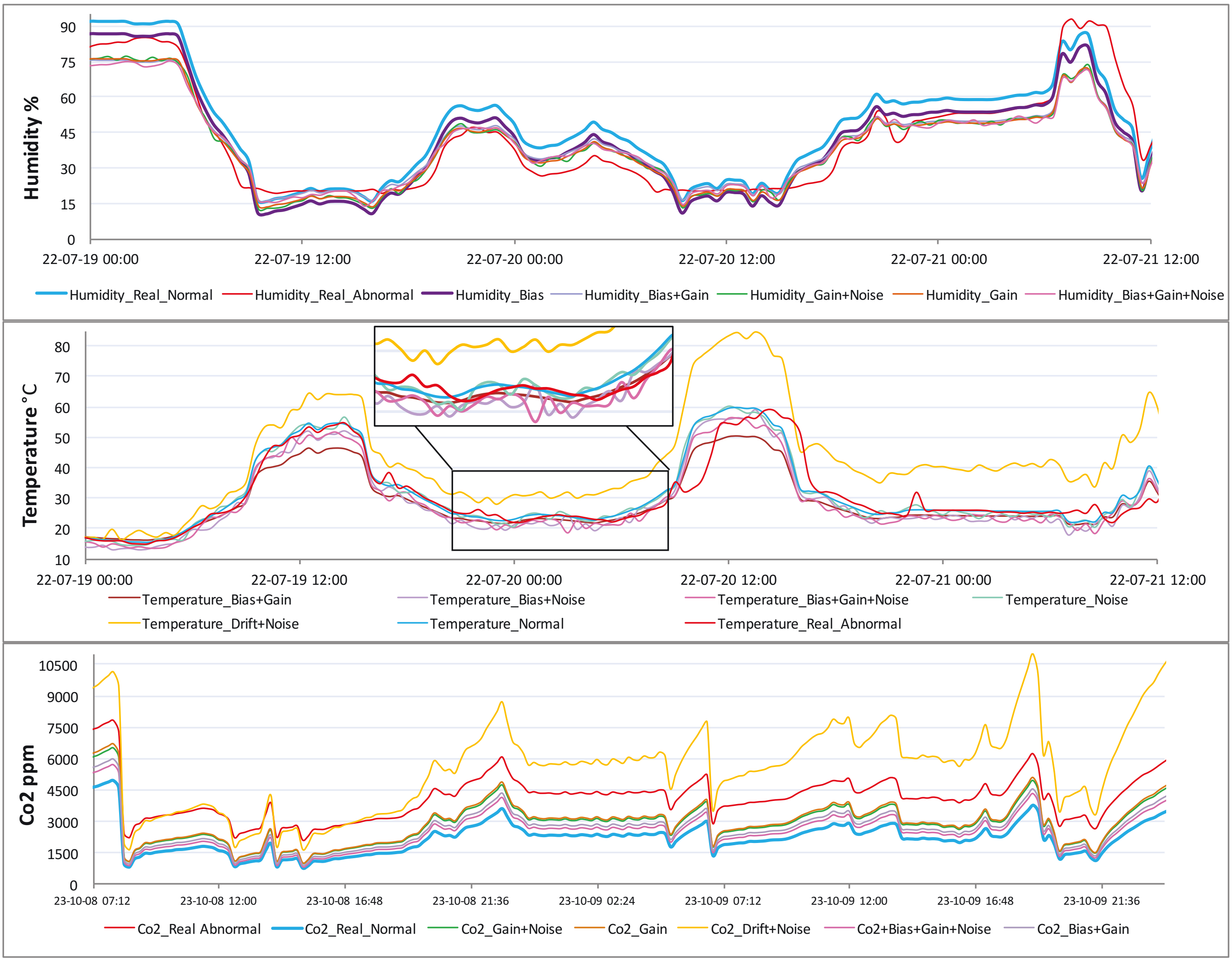

Fig. 2: Illustration of a subset of training sets representing normal and faulty data for humidity, temperature, and CO2

are represented here as equations 8,9,10. True Positive(TP) and True Negative(TN) represent the number of correctly identified normal and abnormal samples. False Positive(FP) and False Negative(FN) represent the number of misclassifications where normal samples are incorrectly identified as abnormal or vice versa. It's crucial to note that, for each fault as anticipated, the classification performance exhibited variation with changing sensor fault magnitudes (e.g., different bias values) for each fault. Consequently, a sensitivity analysis was conducted to understand the impact of these variations. Here, we showcase the optimal classification results achieved by fine-tuning the fault magnitudes specific to each fault.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$F1 - score = \frac{TP}{TP + 0.5 \cdot (FP + FN)} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

Table II presents the results of our experiments, where we trained fault detection models with various humidity training datasets and tested them on real humidity data, including both normal and abnormal values from a degraded sensor. It demonstrates that generating a synthetic training set by modeling fault that includes all fault factors (i.e., noise, bias, and scaling) leads to an improved classification process in a real-world application, allowing for a more precise understanding of sensor behavior. Similarly, Table III delves into the results related to the classification of humidity data when some sensor readings are inaccurate due to external factors causing sensor contamination and malfunction. In this context as well, the integration of all fault factors demonstrates effectiveness in faithfully capturing sensor behavior. Table IV presents classification outcomes on temperature data where the test set encompasses normal and abnormal data from a degraded old sensor. Here, it can be seen the combination of bias (β) and gain (η) for modeling faulty data has the highest accuracy in this case. However, when other parameters (i.e., precision, f1-

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TABLE II: Results of the First Test: Training with Real and Synthetic Faulty Humidity Data, Followed by Testing on Real Faulty Humidity Data (sensor degradation)

Fault in training set \ Classifier method	Accuracy		Precision		F1-score	
	SVM	CNN	SVM	CNN	SVM	CNN
Gain	79.34	83.51	0.7976	0.6151	0.8409	0.7586
Bias	70.48	42.31	0.9461	0.6141	0.6955	0.7573
Noise (Precision degradation)	61.30	61.27	0.6130	0.6136	0.7600	0.7577
Gain+noise	79.132	86.44	0.8105	0.6151	0.8349	0.7583
Bias+noise	61.44	73.06	0.6139	0.6125	0.7601	0.7549
Bias+gain	74.43	63.22	0.7435	0.6130	0.81	0.7565
Drift	61.30	61.19	0.6130	0.6125	0.7600	0.7561
Drift+noise	61.30	61.27	0.6130	0.6130	0.7600	0.7573
Noise+gain+bias	**84.41**	75.30	**0.8457**	0.6130	**0.8776**	0.7566
Real faulty humidity data	85.28	62.28	0.9070	0.6130	0.8758	0.7565

TABLE III: Results of the Second Test: Training with Real and Synthetic Faulty Humidity Data, Followed by Testing on Real Faulty Humidity Data (external interference)

Fault in training set \ Classifier method	Accuracy		Precision		F1-score	
	SVM	CNN	SVM	CNN	SVM	CNN
Gain	77.93	61.38	0.70	0.4386	0.7777	0.6053
Bias	79.31	43.45	0.925	0.4386	0.7115	0.6065
Noise(Precision degradation)	44.13	44.14	0.4413	0.4441	0.6124	0.6116
Gain+noise	77.24	85.52	0.7012	0.4386	0.7659	0.6087
Bias+noise	44.13	52.41	0.4413	0.4441	0.6124	0.6115
Bias+gain	75.17	45.52	0.6666	0.4165	0.7567	0.5746
Drift	44.13	44.14	0.4413	0.4441	0.6124	0.6052
Drift+noise	44.13	44.14	0.4413	0.4441	0.6124	0.6147
Noise+gain+bias	**83.44**	77.24	**0.7702**	0.4386	**0.8260**	0.6093
Real faulty humidity data	84.82	54.45	0.8281	0.4965	0.8281	0.6603

TABLE IV: Results of the third Test: Training with Real and Synthetic Faulty Temperature Data, Followed by Testing on Real Faulty Temperature Data

Fault in training set \ Classifier method	Accuracy		Precision		F1-score	
	SVM	CNN	SVM	CNN	SVM	CNN
Gain	61.44	62.29	0.6291	0.6029	0.7465	0.7477
Bias	38.55	50.85	0.5057	0.6159	0.3776	0.7611
Noise(Precision degradation)	61.86	62.71	0.6186	0.6224	0.7643	0.7646
Gain+noise	61.86	42.37	0.6186	0.6289	0.7643	0.7686
Bias+noise	65.67	66.53	0.6431	0.6159	0.7828	0.7589
Bias+gain	61.86	**66.95**	0.6186	0.6029	0.7643	0.7484
Drift	61.86	62.71	0.6186	0.5964	0.7643	0.7392
Drift+noise	61.86	62.29	0.6186	0.6159	0.7643	0.7593
Noise+gain+bias	65.67	**66.53**	0.6431	**0.6354**	0.7828	**0.7728**
Real faulty temperature data	63.13	61.86	0.6288	0.5964	0.768	0.7406

TABLE V: Results of the fourth Test: Training with Real and Synthetic Faulty Co2 Data, Followed by Testing on Real Faulty Co2 Data (sensor degradation)

Fault in training set \ Classifier method	Accuracy		Precision		F1-score	
	SVM	CNN	SVM	CNN	SVM	CNN
Gain	87.55	54.45	0.9197	0.4965	0.8688	0.6603
Bias	81.25	49.93	0.7632	0.5009	0.8290	0.6655
Noise(Precision degradation)	50.07	50.07	0.5007	0.5014	0.6673	0.6627
Gain+noise	88.00	61.92	0.9440	0.5009	0.8709	0.6638
Bias+noise	50.07	52.47	0.5007	0.5003	0.6673	0.6635
Bias+gain	88.30	62.37	0.9705	0.5012	0.8712	0.6633
Drift	62.81	83.06	0.5757	0.5006	0.7250	0.6626
Drift+noise	86.35	80.06	0.8422	0.5012	0.8679	0.6626
Gain+bias+noise	**88.60**	63.27	**0.9777**	0.5003	**0.8741**	0.6620
Real faulty Co2 data	88.93	91.54	0.9128	0.4965	0.8864	0.6594

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score) are considered, it is clear that having all three factors (i.e., noise, bias, and scaling) in fault simulation resulted in better performance. Lastly, Table V presents the outcomes of testing CO2 data gathered from both normal and degraded sensors, and here, we observe similar trends in the results.

Our experiments reveal that we can markedly improve our capacity to replicate real-world sensor behavior by including multiple fault factors in modeling faults. It underscores the idea that sensor behavior is not invariably straightforward or consistent; rather, it can exhibit complexity in response to different environmental and operational factors. Therefore, our proposed approach suggests that it is important to consider modeling faults by combining different fault factors in addition to the conventional fault modeling approach. This complementary approach can provide a more comprehensive means of replicating real sensor behavior, particularly in cases where sensor malfunctions, such as degradation over time, may result in multiple simultaneous faults and complex variations in sensor readings. Consequently, this can lead to enhanced precision in detecting abnormal data points in real-world sensor observations, which is of utmost importance for maintaining IoT system reliability.

VI. Conclusion

In this paper, we have conducted an in-depth investigation into the modeling faults within time series IoT data. The ultimate aim was to facilitate the development of more efficient and reliable IoT systems by providing an understanding of faulty sensor behaviors (rather than treating them as unknown entities), which, in turn, can lead to enhanced sensor-related fault detection algorithms. Additionally, it facilitates the generation of synthetic data that closely mirrors real-world sensor behaviors, eliminating the need for time-consuming or impractical real faulty data collection. The proposed approach is adaptable to various sensor types and modalities, offering flexibility for broader applications. As a prospective direction for our research, the integration of deep learning techniques, such as generative adversarial networks, into our model has the potential to enhance the quantity and diversity of synthetic data. Deep learning models can be trained using accurate data to generate more high-quality normal data, contributing to the augmentation of datasets. Furthermore, future investigations could explore a broader range of sensors beyond the current narrow domain, contributing to a more comprehensive understanding of the topic.

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