Benchmark Datasets for Fault Detection and Classification in Sensor Data

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Keywords: Benchmark Dataset, Fault Tolerance, Data Quality, Sensor Data, Sensor Data Labelling.

Abstract: Data measured and collected from embedded sensors often contains faults, i.e., data points which are not an accurate representation of the physical phenomenon monitored by the sensor. These data faults may be caused by deployment conditions outside the operational bounds for the node, and short- or long-term hardware, software, or communication problems. On the other hand, the applications will expect accurate sensor data, and recent literature proposes algorithmic solutions for the fault detection and classification in sensor data. In order to evaluate the performance of such solutions, however, the field lacks a set of *benchmark sensor datasets*. A benchmark dataset ideally satisfies the following criteria: (a) it is based on real-world raw sensor data from various types of sensor deployments; (b) it contains (natural or artificially injected) faulty data points reflecting various problems in the deployment, including missing data points; and (c) all data points are annotated with the *ground truth*, i.e., whether or not the data point is accurate, and, if faulty, the type of fault. We prepare and publish three such benchmark datasets, together with the algorithmic methods used to create them: a dataset of 280 temperature and light subsets of data from 10 indoor *Intel Lab* sensors, a dataset of 140 subsets of outdoor temperature data from *SensorScope* sensors, and a dataset of 224 subsets of outdoor temperature data from 16 *Smart Santander* sensors. The three benchmark datasets total 5.783.504 data points, containing injected data faults of the following types known from the literature: random, malfunction, bias, drift, polynomial drift, and combinations. We present algorithmic procedures and a software tool for preparing further such benchmark datasets.

1 INTRODUCTION

Wireless sensor networks (WSNs) are collections of spatially scattered sensor nodes deployed in an environment in order to measure physical phenomena. The data measured and collected by WSNs is often inaccurate: external factors will often interfere with the sensing device. It is then important to ensure the accuracy of sensor data before it is used in a decision-making process (Zhang et al., 2010). Recent literature contributes methods for the detection and classification of sensor data faults (Shi et al., 2011; Ren et al., 2008; Li et al., 2011). One could refer to (Zhang et al., 2010) for a comprehensive survey on fault detection techniques for WSNs. These fault-detection techniques are evaluated by using datasets from an own living lab, e.g., (Warriach et al., 2012; Gaillard et al., 2009), or, more often, using publicly available datasets, such as those published by Intel Lab (IntelLab, 2015), SensorScope (SensorScope, 2015), the Great Duck Island (Mainwaring et al., 2002), and Life Under Your Feet (LifeUnderYourFeet, 2015).

While those datasets greatly support the research community of WSNs in general, to the best of our knowledge, no publicly available datasets are excellent, general benchmark datasets, in which all data points are annotated with the *ground truth*, i.e., whether or not the data point is accurate, and, if faulty, the type of fault and an accurate, "clean" replacement value. Thus, researchers must themselves annotate their dataset in order to obtain the ground truth; different methods of annotating create different ground truths, and annotated datasets are not generally shared. This leads to inconsistencies, even when using the same raw dataset, in the evaluation of fault-detection algorithms: the functional performance of a fault-detection algorithm, measured in the rate of true positives and the rate of false positives obtained when experimenting on an annotated dataset.

To address this issue, in this paper we present

Bruijn, B., Nguyen, T., Bucur, D. and Tei, K.
Benchmark Datasets for Fault Detection and Classification in Sensor Data.
DOI: 10.5220/0005637901850195
In *Proceedings of the 5th International Confererence on Sensor Networks (SENSORNETS 2016)*, pages 185-195
ISBN: 978-989-758-169-4

Table 1: Overview of the benchmark datasets.

	Missing values	Fault types	Sensor types	Placement	Data samples	Number of sensors
Intel lab	non-interpolated and interpolated	clean, random, malfunction, bias, drift, polynomial drift, mixed	temperature and light	indoors	3.980.192	10
SensorScope	non-interpolated and interpolated	clean, random, malfunction, bias, drift, polynomial drift, mixed	temperature	outdoors	1.063.641	10
Santander	non-interpolated and interpolated	clean, random, malfunction, bias, drift, polynomial drift, mixed	temperature	outdoors	739.671	16

a standardised approach to prepare such annotated benchmark datasets, including 1) cleaning a dataset, and 2) injecting faults to obtain an annotated dataset with a selection of faults. Figure 1 gives an overview of our data benchmarking process, from raw sensor data to fault-annotated data.

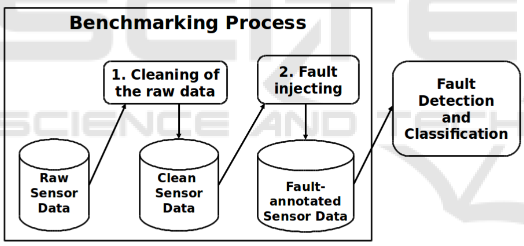


Figure 1: The process of preparing a benchmark dataset.

As the first step, we briefly discuss methods for cleaning a raw dataset in order to obtain a dataset without faulty readings; here, no perfect, general cleaning method exists, and we rely, as also most of the literature, on visual inspection and some domain knowledge. After obtaining a clean dataset, we propose and implement a tool for fault injection based on the general fault models proposed by (Baljak et al., 2013). This categorisation is based on the frequency and continuity of fault occurrences and on observable and learnable patterns that faults leave on the data. The models are flexible and applicable to a wide range of sensor readings. The type of the injected faults is annotated in the transformed dataset, allowing easier and meaningful analysis and comparison during algorithm assessment.

The major contributions of this paper are summarised as follows:

- Methods and algorithms to inject faults in clean datasets on demand based on a generic fault model.
- Software for the injection of artificial faults in datasets, supporting users to flexibly create their own annotated sensor dataset on demand.
- Three large annotated benchmark datasets generated from the Intel Lab (IntelLab, 2015), SensorScope (SensorScope, 2015) and the Smart Santander (SmartSantander, 2015) deployments, using our method. The datasets include in total 644 subsets of 5.783.504 annotated readings, injected with a mix of various fault types.

From the Intel Lab raw data, we extract one week of temperature and light measurements from each of 10 sensors. The raw data is first cleaned, then we inject faults. There are 120 fault-injected sets in total: 10 nodes with each six sets for temperature and six sets for light. The faults injected are 1) random, 2) malfunction, 3) bias, 4) drift, 5) polynomial drift, and 6) mixed faults. From SensorScope we use ambient temperature data from 10 nodes, resulting in 10 clean datasets and 60 fault-injected datasets using the same six types of faults as for Intel Lab. The third benchmark dataset is constructed from a new, previously unpublished sensor dataset, consisting of temperature measurements from 16 outdoor sensors that are part of the Smart Santander project (SmartSantander, 2015). This consists of 16 clean datasets and 96 fault-injected datasets. Furthermore, we offer the datasets in both *interpolated* and *non-interpolated* form: the non-interpolated dataset uses the original timestamps and any missing data points are not replaced, whereas the interpolated datasets fill in a measurement for each missing value. Table 1 presents an overview of the benchmark datasets.

The remainder of this paper is structured as follows: Section 2 explains what types of faults are commonly found in wireless sensor data, and how these faults can be modelled, followed by Section 3 that discusses the annotation challenges for such dataset and the proposed approach for benchmarking. Section 4 shows how we obtain a benchmark dataset by applying our proposed procedure and the software tool. Finally, we conclude the paper in Section 5.

2 BACKGROUND ON FAULT MODELS IN SENSOR DATA

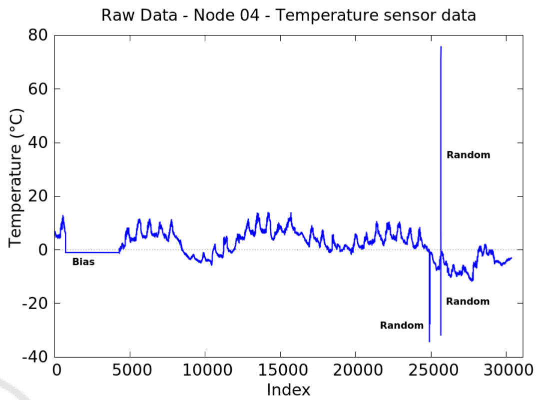
As the first step of fault management, it is crucial to categorise faults. On one hand, by comprehending the causes, effects, and especially the characteristics of each fault type onto the data it is possible to propose suitable fault-tolerance mechanisms to detect, classify, and correct data faults of each type. This knowledge is also necessary to clean the dataset and to design functions to inject faults of each type.

2.1 Types of Faults

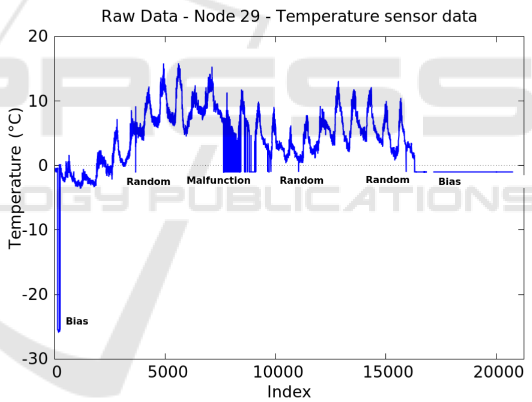
Fault categorisation techniques vary: several existing fault taxonomies use different criteria for categorising a fault. (Ni et al., 2009) give extensive taxonomies of data faults that include a definition, the cause of the fault, its duration and its impact onto sensed data. According to the authors, sensor faults can be classified into two broad fault types: 1) *system faults* and 2) *data faults*. From a system-centric viewpoint, faults may be caused by the way the sensor was calibrated, a low battery level, the clipping of data, or an environment-out-of-range situation. On the other hand, data faults are classified as *stuck-at*, *offset*, or *gain* faults. These same three types of data faults are denoted *short*, *constant*, and *noise*, respectively, by (Sharma et al., 2010).

2.2 Fault Models

(Baljak et al., 2013) proposes a complete, general categorisation based on the **the frequency and continuity of fault occurrence** and on the **observable and learnable patterns** that faults leave on the data. This categorisation is flexible, and applicable to a wide range of sensor types. The underlying cause of the error does not affect this categorisation, which makes it possible to handle the faults solely based on their patterns of occurrence on each sensor node. Examples of several fault types are given in Figure 2. Note that the figures in this paper display values that are not necessarily uniformly sampled. While in theory the sensors report values regularly, reality shows that quite many values are missing. The gaps that as a result exist, are usually too small to be visible on the graphs. Section 4.2 treats this subject in more detail.



(a) One bias and three random faults.



(b) One short duration bias, one long duration bias, one malfunction and three random faults.

Figure 2: Examples of random, malfunction, and bias faults taken from the SensorScope dataset, motes 4 (a) and 29 (b).

(Baljak et al., 2013) defines the following models of data faults:

- **Discontinuous** – Faults occur from time to time, and the occurrence of faults is discrete.
  - **Malfunction** – Faulty readings appear frequently. The frequency of the occurrences of faults is higher than a threshold τ.
  - **Random** – Faults appear randomly. The frequency of the occurrences of faulty readings is smaller than τ.
- **Continuous** – During the period under observa-

tion, a sensor returns constantly inaccurate readings, and it is possible to observe a pattern in the form of a function.

– **Bias** – The function of the error is a constant. This can be a positive or a negative offset.

– **Drift** – The deviation of data follows a learnable function, such as a polynomial change.

The fault categorisation in (Baljak et al., 2013), (Ni et al., 2009) and (Sharma et al., 2010) do overlap. The fault types can be mapped, as depicted in Table 2, into one fault or a combination of faults defined using the other approaches.

An important note about terminology is in order. Sometimes an outlier is not necessarily a faulty value, it may be the manifestation of something interesting happening in the environment. This is not so likely in case of for example bias faults, but for random faults this may very well be the case. Distinguishing between faulty values and interesting events is a difficult subject. For this paper we will use the term fault, and leave it to the users of the datasets to use them as faults, or as anomalies.

Table 2: Relationships between fault models.

(Baljak et al., 2013)	**(Ni et al., 2009)**		**(Sharma et al., 2010)**
	Data-centric	**System-centric**	
Random	Outlier		Short
Random or Malfunction	Spike	Hardware Low Battery	Short
Bias	Stuck-at	Clipping Hardware Low Battery	Constant
Drift	Noise	Low Battery Hardware Env. out of range	Noise
Bias or Drift		Calibration	Noise

3 ANNOTATION CHALLENGES AND APPROACH

Two main steps that have to be performed in order to prepare the dataset for usage are 1) *cleaning the raw data* and 2) *injecting artificial faults*. Cleaning the data is necessary to ensure that the fault detection algorithms are only executed on known faults, allowing for consistent evaluations. After that, new faults may be injected. The proposed fault injection method allows for injecting faults flexibly, as required by the use case. In the following subsections we explain the two main steps in more detail.

Table 3: Dataset cleaning techniques in literature.

	Visual inspection	Run scripts to annotate	Domain knowledge	No cleaning	No mention of cleaning
(Ni et al., 2009)					√
(Hamdan et al., 2012)				√	
(Nguyen et al., 2013)	√	√			
(Baljak et al., 2013)				√	
(Sharma et al., 2010)	√		√		
(Warriach et al., 2012)				√	
(Ren et al., 2008)				√	
(Yao et al., 2010)	√				

3.1 Data Cleaning

The main challenge in cleaning the dataset is the fact that the process can not be fully automated, as no general, "perfect" method of detecting sensor data faults exists. We survey multiple studies in order to obtain an overview of the data cleaning techniques used in the field.

3.1.1 Case Studies

Eight studies are surveyed in order to find the most common techniques used to clean datasets. Table 3 summarises the results. Most studies do not actually clean the dataset of faults, or they do not formally describe any cleaning method. Out of the data cleaning techniques, visual inspection is the most commonly used: by three out of eight studies. Some mention running scripts to annotate the data, although no algorithm is described. Some authors employ domain knowledge on top of visual inspection, which may increase the likelihood that faults are spotted, as domain experts are more familiar with the underlying phenomenon and thus are more capable in distinguishing normal data from faults.

3.1.2 Cleaning Guidelines

(Sharma et al., 2010), (Nguyen et al., 2013) and (Yao et al., 2010) use visual inspection to clean datasets. A visual presentation of the data can help in locating faults in large datasets. The human visual perception system is well equipped to spot high-intensity faults residing in a low-variance phenomenon such

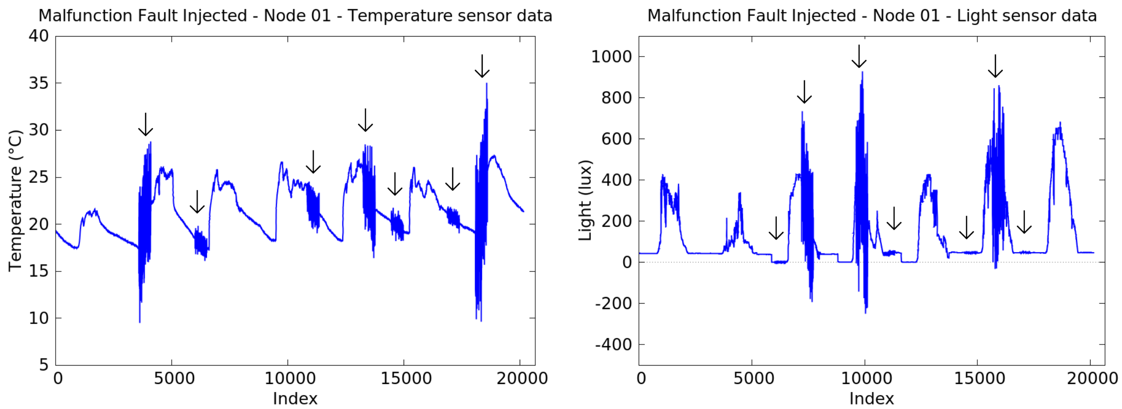


Figure 3: Injected malfunction faults in both temperature and light data, indicated by small arrows. Intel dataset, node 1, interpolated.

as temperature. However, low-intensity faults residing in a high-variance phenomenon such as light are much harder to spot. This visual inspection is best performed by a domain expert, as he will be better able to accurately distinguish regular sensor readings from interesting events and data faults.

Once one or more data faults have been identified, the data preprocessor needs to decide how to remove them. There are two distinct cases. In case the fault is of short duration, typically less than 10 values, the faulty values can be easily replaced by *interpolating* between the two correct values at both sides of the interval. Removing the faults becomes more complicated when the duration of the faulty interval is longer, or when the phenomenon is high-variance. This is due to the fact that more information is absent as the duration increases, making any estimation of the original correct value increasingly error prone. Add to that the fact than some fault-detection methods (such as those based on time-series analysis) rely on the fact that the data is measured at equispaced time intervals, and simply removing the faulty values will pose problems.

There are several ways the data preprocessor can remove long-duration faults. It could replace the entire interval with a constant value. This, however, effectively introduces a bias fault. Alternatively, some variable offset can be added to this constant value, or the data preprocessor could replace it with a frame of readings with somewhat similar values. Of course, it is safest to not use these intervals at all. There is no certain way of telling what the faulty values should be corrected to, and attempting to reconstruct long intervals reduces the integrity of the dataset by introducing artificial values. In our experience, real world datasets will start to display more long-duration faults as the lifetime of the sensor nodes increases. With this in mind, the best approach is to use sensor data that was reported before the sensor started to decay.

3.2 Fault Injection

For this paper we choose to use a percentage-based interval division of the data set. This allows the users of our proposed tool to precisely specify what parts of the dataset are to contain certain faults, while still providing a layer of abstraction over the temporal distribution of the data. Four vectors, s_r, s_m, s_d, and s_b, each contain a number of pairs specifying the start and end of the intervals of their respective faults: random, malfunction, drift or bias. These values are percentages. An example vector is: $s_r\{(4,6),(12,15)\}$; it specifies that random faults are to be injected in the data samples between the first four and six percent of the dataset, as well as between percentages twelve and fifteen. This concept is best illustrated by a figure. Figure 3 displays a dataset where malfunction faults have been injected into the clean data of node 1 from the Intel Lab dataset for both temperature and light. The small arrows indicate where malfunction faults have been injected, notice that some faults are much more subtle than others. The faults are only injected in the user-specified intervals. All four different faults specified by Baljak's fault models can be injected in this fashion, each one having its own parameters to allow maximum flexibility.

The injection algorithms apply the fundamental work done by (Sharma et al., 2010). The algorithms annotate the data with the faults that are injected; this is an added column to the dataset that stores the ground truth for each measurement. In the following, we explain in more detail how the four types of faults can be injected. Note that the following algorithms (algorithms 1 to 4) are applied to the data samples in one of the aforementioned intervals (a pair in s_r, s_m, s_d or s_b). In other words, the algorithms are applied to

Table 4: Overview of variables and parameters.

Name	Description
s_r	set of intervals for random faults
s_m	set of intervals for malfunction faults
s_d	set of intervals for drift faults
s_b	set of intervals for bias faults
δ_r	density (percentage) of random faults in the intervals
i_r	intensity vector for random faults
n_m	noise intensity parameter for malfunction faults
i_d	intensity vector for drift faults
n_d	noise intensity parameter for drift faults
n_b	noise intensity parameter for bias faults
i_b	intensity vector for bias faults
m_b	mean value for bias faults
S	subset of the clean data
I	vector containing (value, annotation) pairs representing an annotated, fault-injected version of S

a subset of the clean dataset. This subset is denoted by S. It is not specific to any fault type, it is merely a representation of some subset of the clean data. Table 4 summarises the used variables and parameters.

3.2.1 Random Fault

Random faults often occur in an isolated fashion. We propose a method that allows injecting random faults with a user-specified density, δ_r, in the data samples from an interval in s_r. These data samples are denoted by S. The density parameter δ_r determines the percentage of readings within S that are to be a random fault. Let k be some index for S. A value S_k in S is transformed into an annotated random fault I_k based on formula 1:

$$I_k = (S_k(1 + intensity), \text{“}random\text{”}) \tag{1}$$

where *intensity* is a value from the vector of intensities, specified by the user as parameter i_r. A random intensity is chosen from i_r for each fault. This is implemented in Algorithm 1.

3.2.2 Malfunction Fault

Malfunction faults do not rely on a density parameter, as they typically affect all readings within an interval. Malfunction faults are defined as an interval of measurements that display a higher variance than normal. To recreate this increased variance, we compute the variance over the original measurements in S: $\sigma_{original}$. This is then used to obtain a value from the normal distribution with mean zero and the computed

Algorithm 1: Injecting Random Faults.

Input: $S[1..N]$: subset of the clean dataset, a vector of N measurements
δ_r: density parameter
i_r: intensities vector
Output: $I[1..N]$: vector of (value, annotation) pairs representing N annotated random-fault-injected sensor readings

for i = 1 to N **do**
  $p \leftarrow$ random percentage $\in [0,100]$
  $r \leftarrow$ random index $\in [1,|i_r|]$
  if $p > \delta_r$ **then**
    $I[i] \leftarrow (S[i],$ *“clean”*$)$
  else
    $newValue \leftarrow S[i] * (1 + i_r[r])$
    $I[i] \leftarrow (newValue,$ *“random”*$)$
  end if
end for
return I

variance, which is then multiplied by a user-specified intensity, n_m. This new value is added to the original value to obtain the injected fault:

$$I_k = (S_k + \mathcal{N}(0, \sigma^2_{original}) * n_m, \text{“}malfunction\text{”}) \tag{2}$$

Note that we model malfunction faults by making an assumption as to the expected probabilistic distribution of malfunction faults. However, we have no concrete knowledge as to which distribution gives the most accurate model for a particular type of faults and a particular type of sensor; we chose a normal distribution as the most likely.

This method for the injection of malfunctions is implemented in Algorithm 2.

Algorithm 2: Injecting Malfunction Faults.

Input: $S[1..N]$: subset of the clean dataset, a vector of N measurements
n_m: noise intensity parameter
Output: $I[1..N]$: vector of (value, annotation) pairs representing N annotated malfunction-fault-injected sensor readings

$v \leftarrow$ variance of S
for i = 1 to N **do**
  $newValue \leftarrow S[i] + \mathcal{N}(0, v^2) * n_m$
  $I[i] \leftarrow (newValue,$ *“malfunction”*$)$
end for
return I

3.2.3 Drift Fault

Drift faults can be injected in multiple ways. One way to do it is by using a polynomial to model the drift fault. The polynomial consists of a number of coefficients: $a_0, \dots, a_n$, and a number of variables: $x^0, \dots, x^n$. The summation of their products forms the polynomial model. Substituting x for k and adding the original value from S, we obtain the following equation for the new value:

$$I_k = (S_k + \sum_{i=0}^{n} a_i k^i, \text{“}\textit{poly-drift}\text{”}) \quad (3)$$

Another method that deviates from Baljak's fault models is by injecting drift faults as a sequence of values with an offset to the original data, with some variance added to it. The formula for this method is as follows:

$$I_k = (S_k + \mathcal{N}(0, \sigma^2_{original}) * n_d + \mathit{offset}, \text{“}\textit{drift}\text{”}) \quad (4)$$

The offset is obtained by taking the first measurement from the interval and multiplying it with a random intensity from the user-specified intensities i_d. n_d determines the amount of noise that is added to the drift fault. Formula 4 is implemented in Algorithm 3.

Algorithm 3: Injecting Drift Faults.

Input: $S[1..N]$: subset of the clean dataset, a vector of N measurements
i_d: intensities vector
n_d: noise intensity parameter
Output: $I[1..N]$: vector of (value, annotation) pairs representing N annotated drift-fault-injected sensor readings

```
r ← random index ∈ [1,|i_d|]
v ← variance of S
offset ← S[1] * i_d[r]
for i = 1 to N do
    newValue ← S[i] + N(0, v^2) * n_d + offset
    I[i] ← (newValue, “drift”)
end for
return I
```

3.2.4 Bias Fault

A bias fault is defined as a number of measurements that display little to no variance, usually accompanied by some offset to the expected value. There are two ways to inject a bias fault, both have the option to add some variance with intensity n_b:

1. Supply a value m_b that is to be used as the new mean:
$$I_k = (m_b + \mathcal{N}(0, \sigma^2_{original}) * n_b, \text{“}\textit{mean-bias}\text{”}) \quad (5)$$
2. Supply a factor i_b that will be multiplied with the original mean of the measurements in the time frame:
$$I_k = (i_b * \mu_{original} + \mathcal{N}(0, \sigma^2_{original}) * n_b, \text{“}\textit{bias}\text{”}) \quad (6)$$

Formula 6 for injecting bias faults is implemented in Algorithm 4.

Algorithm 4: Injecting Bias faults.

Input: $S[1..N]$: subset of the clean dataset, a vector of N measurements
n_b: noise intensity parameter
i_b: intensities vector
Output: $I[1..N]$: vector of (value, annotation) pairs representing N annotated bias-fault-injected sensor readings

```
r ← random index ∈ [1,|i_b|]
v ← variance of S
o ← original mean of S
newMean ← o * i_b[r]
for i = 1 to N do
    newValue ← newMean + N(0, v^2) * n_b
    I[i] ← (newValue, “bias”)
end for
return I
```

4 THE DATASET

We implement the fault injection methods in Java. A publicly available release of the three datasets is available at http://tuananh.io/datasets.

4.1 Cleaning Raw Data from the Datasets

We visually inspect the raw data time series to identify the characteristics of correct readings, as well as those of random, malfunction, bias, and drift faults. The approach for cleaning the Intel Lab dataset is slightly different from the one used for SensorScope. For the Intel Lab dataset, we determined that the first week was free of long-duration faults for all nodes, and thus decided to select the readings from this interval for our benchmark dataset. Figure 4 shows the selected first week of clean data from node 1 of the Intel Lab dataset. Note that the gaps are clearly visible, these are points where values are missing. The short-duration faults are manually removed by interpolating between the correct neighbouring values. The SensorScope dataset contained some nodes that displayed long-duration faults within the first week of deployment. In this case we decided to select the readings from a custom interval for each node, up until the first long duration interval is present. The consequence is that some of the cleaned nodes contain more readings than others. Again we removed the short-duration fault by hand, by interpolating between the

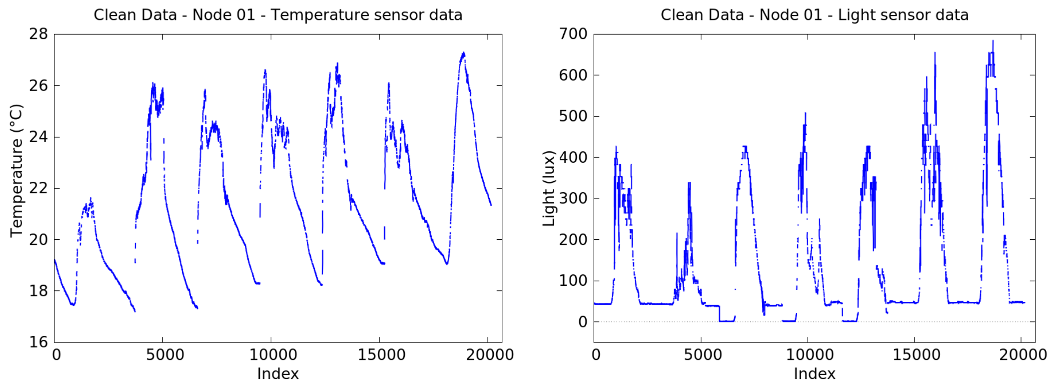


Figure 4: Clean temperature data (left) and light data (right) from mote 1 of the Intel Lab dataset.

neighbouring values. For the Smart Santander dataset we selected a period of data of about two weeks that was free of faults. In all three cases we have relied mainly on a smart selection of data subsequences, so as to minimize the amount of faults that have to be removed.

4.2 Uniform Data Frequency

Some fault detection methods, such as seasonal Auto-Regressive Integrated Moving Average (ARIMA) (Nguyen et al., 2013; Box et al., 2013), call for a fixed number of data samples in a certain period, or season. The three datasets in their original form contain many missing values, which interferes with these methods. Because sensor technologies continue to improve, we expect that missing values will become rarer in the future.

It is for these reasons that we provide the benchmark datasets in two forms: the first form uses the timestamps and measurements from the original dataset, and thus has missing data points. The second form ensures that a measurement is present for each expected timestamp. For example, if the sensor is supposed to report a measurement every five minutes, the datasets of the second form will contain a measurement for every five minutes within the interval. If a timestamp is missing, a new data sample will be created with the measurement interpolated in a linear fashion.

4.3 Annotated Fault-Injected Datasets

The implementation details of the four algorithms are presented in Algorithms 1 to 4. The parameters used for the algorithms are listed in the algorithm listings. These parameters are obtained through trial and error; we adjusted them until they resulted in the best representation of real world faults for these types of sensed data. Note that these parameters work for these particular datasets, they may not necessarily work for all datasets. So while the method for injecting faults is general, the parameters will often be specific to the datasets.

Table 5: Algorithm parameters.

δ_r	0.2
i_r	$(1.5, 2.5)$
n_m	1.5
i_d	$(-2, -1, 1, 2)$
n_d	2.0
n_b	0
i_b	(1.5)

In the provided benchmark datasets, the percentage of faulty readings differs per fault type. In case of injected drift faults, 20% of the readings are faulty. In case of injected random faults 20% of the dataset is affected by random faults. The intervals that are affected by random faults in turn have a density of 20% faults, resulting in 4% of actual random faults. Bias and malfunction faults are both injected in 21% of the readings, while the mixed datasets consist of 4% random faults[1], 4% drift faults, 6% malfunction and 6% bias faults. Figure 5 graphically illustrates datasets with faults injected of types random, drift, polynomial drift, bias and mixed fault types. These are injected over the temperature and light sensor data of node 1 from the Intel dataset (shown in Figure 4).

[1]Note that again, this means that 4% is affected by a random fault and 20% of this 4% is an actual random fault, resulting in 0.8% actual random faults.

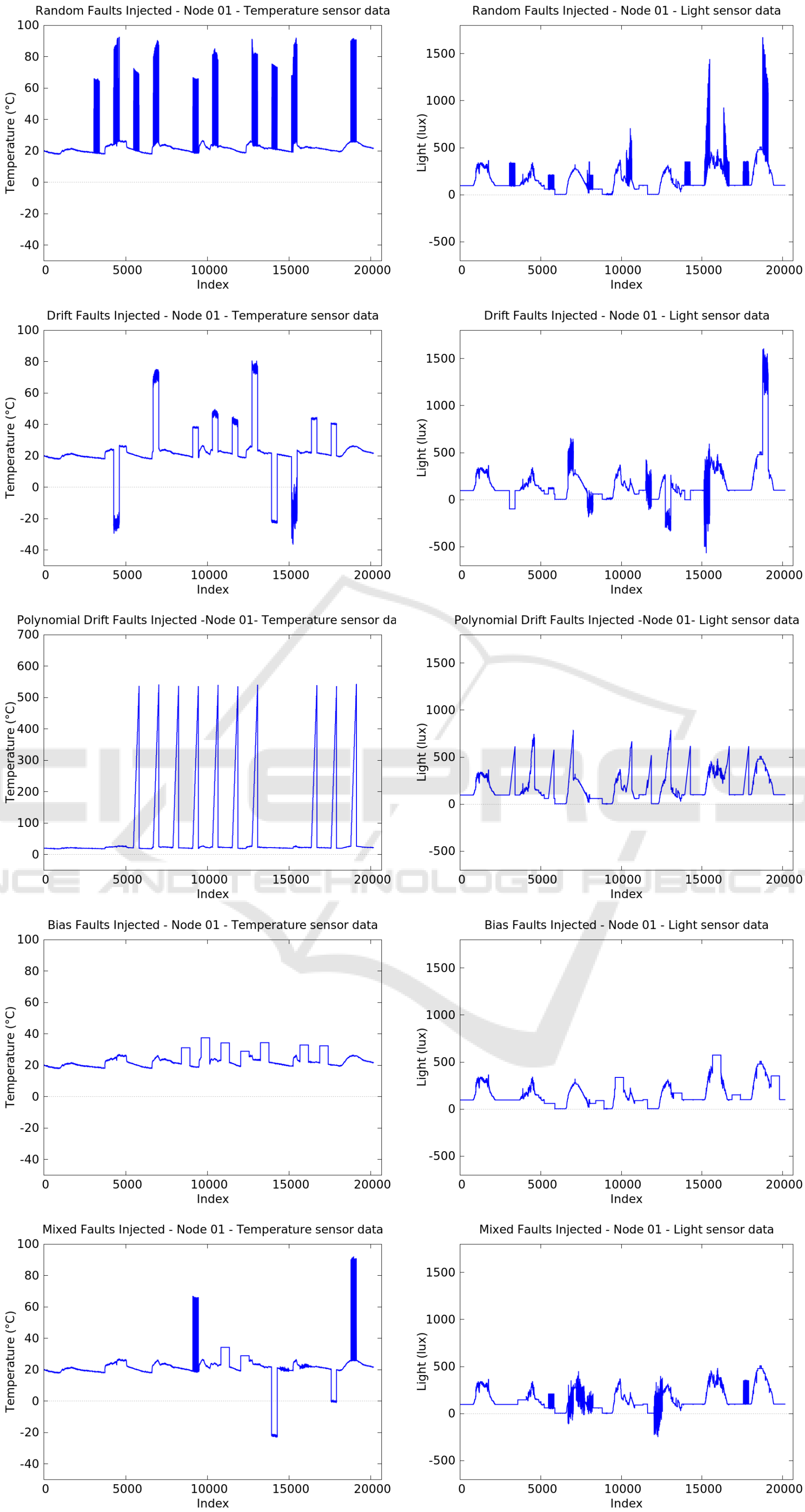


Figure 5: Five different fault types injected in node 1 of the Intel Lab dataset *(left: temperature sensor data; right: light sensor data).* Interpolated data.

5 CONCLUSIONS, DISCUSSION, AND FUTURE WORK

Summary of Contribution and Critical Discussion. The literature does not currently give a *structured* methodology for cleaning a raw dataset of sensor readings, and especially obtaining an *annotated* dataset of readings which includes data faults in configurable patterns. Without this methodology, studies which design and evaluate algorithms for anomaly detection, classification, and correction in sensor data is difficult to evaluate comparatively.

Cleaning a given dataset is ideally done via the resource-heavy process comparing the sensor data against data acquired concurrently by a second, calibrated, high-fidelity sensor, which is able to collect digital data, and either download it over a network, or store large datasets in memory. However, an ideal such second sensor is rarely available in real-world deployments, and arguable all the sensor datasets currently available for experimentation have been cleaned via an unstructured process which combines a degree of domain knowledge with a form of basic inspection of the data. This process is error-prone, and may not differentiate (for all types of physical phenomena sensed) between legitimate faults in the data and true anomalous conditions in the environment. Other means for classifying raw data points are surveyed in (Zhang, 2010).

This paper does not contribute a data-cleaning methodology, but provides a framework to prepare annotated datasets with configured injected faults, which are well suited for then evaluating fault-detection methods. The framework requires a clean dataset in the input. The datasets we publish here have used as clean data some subsets of raw datasets which we have judged, using our own domain knowledge and visual inspection, to have been the least affected by faults in the sensing system, and which thus required minimal manual cleaning and interpolation for missing values.

We provide three benchmark datasets for the evaluation of fault detection and classification in wireless sensor networks, and a Java library which implements configurable fault-injection algorithms. The first benchmark dataset includes 280 subsets of temperature and light sensors of 10 nodes extracted from the Intel Lab raw data. The second benchmark dataset includes 140 subsets of ambient temperature sensors extracted from the SensorScope dataset. The third benchmark dataset includes 224 subsets of temperature measurements obtained from 16 sensors as part of the Smart Santander project. The three benchmark datasets total 5.783.504 data samples, covering six types of faults that have been observed in sensor data by prior literature. Faults are injected using known, generic fault models. We publish the datasets at http://tuananh.io/datasets. We believe that all papers listed in table 3 would have benefited from using such annotated datasets.

This paper attempts an initial, systematic treatment of the problem of the missing annotated datasets. Its main limitation lies in the fact that the annotated datasets have been obtained based on cleaned sensor data that is still not entirely guaranteed to be free of all faulty readings.

Future Work. We plan to extend the current datasets two-fold: (a) by processing and publishing sensor datasets pertaining to physical phenomena other than light and temperature, and (b) by preparing annotated datasets based on cleaned datasets with a better guarantee of correctness. Also, we aim at developing a software tool of a user-friendlier nature, for configuring the fault injection algorithms.

ACKNOWLEDGEMENT

The work is supported by 1) the FP7-ICT-2013-EU-Japan, Collaborative project ClouT, EU FP7 Grant number 608641; NICT management number 167 and 2) the Dutch National Research Council Energy Smart Offices project, contract no. 647.000.004 and 3) the Dutch National Research Council Beijing Groningen Smart Energy Cities project, contract no. 467-14-037.

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