

Behavioral Irregularity Signatures in Low-Power IoT Sensor Streams: A Lightweight Cross-Dataset Investigation of Anomaly Patterns in Real Environmental Networks

Raafat Talib Hashim

Department of Computer Technical Engineering, Imam Al-Kadhum College, Baghdad, Dhi Qar, Iraq.

Abstract: The low-power IoT sensor streams in environmental networks are characterized by complex physical processes, various measuring modalities and rich temporal dynamism. Sparse sensors would like to send low-rate volume records subject to time and space constraints. Behavioral anomalies, with anomalous (i.e., atypical) increments to an otherwise pristine low-activity pattern, emerge as a heuristic compact description of these data streams. The visible granularity in atomic behavior indicates that an irregularity-driven representation might support lightweight cross-dataset theoretical examination of anomalous behaviors. The environmental communities have been identified from three datasets: Intel Lab Data, SensorScope and Gas Sensor Array Drift -- which capturing similar streams. A behavioral anomaly characterization for low power IoT traffic is presented in conceptual terms. Sensor streams possess features associated with their environmental nature which anomalies are based on, therefore causing a general observational interest. Anomalies are handled qualitatively through the framework of theoretical modeling that allows to adopt a common language for irregularity signatures rather than to include dataset-specific empirical numbers.

Keywords: Low-Power, IoT, Environmental phenomena, Sensor.

INTRODUCTION

Anomalies in low-power IoT sensor streams appear as abstract signatures that cut across multiple temporal scales. They are caused by environmental phenomena, sensor offset and transmission artifacts. Although hardware, environment and underlying driver different length set up, there appear cross-dataset commonalities of the occurrence and patterns of specific anomalies in many real-scale networks. (Lightbody *et al.*, 2024)

Real deployment experiments with data generated from IoT devices (rather than synthetic sources) have become a viable approach to study low-power sensor operation and behavior in realistic environments. Fundamental assumptions regarding sensor dynamics, energy budget, and communication model determine the kind of irregularity signatures that we observe. Information from diverse environment domains reveals four main classes of irregularity: patterns, bursts, drifts and intermittent anomalies. These conceptual constructs capture several distinctive aspects and exhibit reasonable invariance across diverse datasets. (Sklenář *et al.*, 2022)

A significant number of such authentic environmental networks have the common property that they are duty-cycled and they operate in low-power mode. Company Introduction Environmental sensors receive a mixture of fluid, temperature, humidity and noise signals. Investigation on several cross-sensor studies has

resulted in the proposal of a minimal annotation scheme comprising six stability, three noise-level and three long-range-dependence classes. Though we give no specific values for the experimental data, the form of the operational periodicity is regular enough to be a potential anomalous driver present in multiple data sets. (Cerar *et al.*, 2020).

THEORETICAL FOUNDATIONS

Anomaly detection has become a critical research field in the Internet of Things (IoT) due to its contributions to securing, managing, and optimizing sensor networks. A number of theoretical frameworks have been offered, to understand its nature and to suggest possible models. However, the analysis of low-power sensor streams is complexly coupled to individual data sets and it remains difficult to give general assessments. Three interrelated questions served as the basis of a conceptual analysis of the nature of behavioral irregularities in low-power streams that appear coherent across datasets in their expression. For low power sensor streams, clear limits are posed by strict energy budgets becoming a bottleneck in terms of adaptation speed, sampling regime and operation times. As a result, irregularity signatures manifest as certain properties—temporal, structural, robustness and qualitative—that are conjectured to be common across different environments. Formal models of anomaly patterns at these dimensions, articulated with reference to empirical feature sets, are

theoretically outlined to facilitate generalization to additional datasets. (Yang and Zhang2023)

Low-Power IoT Sensor Streams

The general features of low-power Internet-of-Things (IoT) sensor streams can be characterized under four aspects: sampling regime, duty cycling, resources, and noise resilience. These streams typically adopt hourly or daily sampling, monthly or wider duty cycling, and are severely restricted in energy, memory, and processing resources. They can tolerate significant amounts of noise without affecting their regularity signatures ((Weihong) Han *et al.*, 2019).

Most low-power IoT sensor streams have either symmetric or asymmetric (positive or negative) deviations from regularity. The deviation signature exhibits strong multi-scale structures, meaning that each deviation pattern is framed within multi-scale sampling contexts. The deviation signatures of some streams remain remarkably unchanged despite large sampling perturbations, indicating that these streams have fragile signatures. The scattered readings of many real environmental networks form the core of all-time and a representative set of mainstream datasets. Many networks share identical structures, whereby generic environmental drivers, specific layouts, and mechanisms cause different responses under diverse settings. Therefore, the anomaly signature manifests differently; some studies observe bursts of similar irregularity in distinct datasets, while others document opposite patterns. (Arif *et al.*, 2024)

Behavioral Irregularity Signatures

Irregularities measured at various temporal scales reveal large deviations from expected observations resulting from distinct underlying physical and contextual phenomena. We conceptualize four interrelated motifs that correspond to the presence, frequency, and intermittency of these significant deviations: a pattern irregularity characterizes shifts in expected trajectories depending on anticipated developments; a burst irregularity accounts for increased occurrence rates of deviations; a payload drift indicates gradual alterations of measurements linked to a slow-changing contextual aspect; and an intermittent irregularity signals sudden changes in the periodic activation of a system. Together, these motifs delineate a wide behavioral spectrum commonly observed in environmental networks, and we find they exhibit cross-dataset invariance despite different observed dimensions, systems of interest,

and environmental factors. The Gas Sensor Array Drift and SensorScope networks investigate distinct processes yet still display similar sensitivity to context shifts around the same time, illustrating the potential prevalence of these four motifs across independent low-power IoT setups (Cerar *et al.*, 2020).

Low-power IoT networks conform to a few general principles, including periodic sampling, duty-cycling, heterogeneous communication protocols, and lower delivery expectations, depending on the specific implementation. Temporal intervals between reported measurements tend to be considerably shorter than the overall duration of the acquisition mechanism; a dormant period may span several days, yet individual measurements still occur within minutes or seconds. Behavioral irregularities, therefore, arise on relatively long timescales often exceeding classical definitions. Further, channel saturation, resource conservation, and energy awareness already limit the generation of large volumes of streams, pushing the number of lower-dimensional supporting observations down. Periodic query structures involving multiple queries per sampling phase nonetheless continue to determine the expected timing of new data, a situation further complicated by other temporal dependencies among active low-power realizations, e.g., sleep and wake cycles tied to energy supply. (Majhi & Mohanty, 2024)

Anomaly Patterns in Real Environmental Networks

Understanding low-power Internet of Things (IoT) phenomena necessitates awareness of sensorial-behavioral irregularities generated by real environmental operational systems—behaviors worth observing, especially when operating off hours. Low-power cycles influence sensing, transmission, and communication. Yet, even in small, low-power micro-bursting, certain behavioral motifs appear. The emphasis shifts to irregularity signatures rather than higher-level metrics, materializing at much shorter timescales than those linked with traditional interest in contaminants. The focus lies on the transferability of knowledge in operational-space sensory-behavioral irregularities that characterize real, observable, performance-driven, and economic low-power sensing and communication systems. (Zhao and Lian2022)

Within mainstream IC metrics of quality, integrity, and reliability, this low-power operational-space

analysis highlights within a thoroughly condensed functional envelope the significant role performed by obscure, low-level functional process phenomena. Standard radio frequency design constraints center on substantial economic obstacles concerning—but yet extensive, generic behavioral-based operational-space understanding beyond the IC level. Interest resides within the common-sense proposition that low-power systems are not switched-off at night but rather undergo important, observable, and transferable behavior change replacing a daytime operational function with a different function during much reduced night periods to just re-affirm the obvious. (Stock *et al.*, 2024)

RELATED WORK

Behavioral irregularities in low-power IoT sensor streams remain inadequately explored, notably regarding cross-dataset commonalities and divergences. Such logs encode time-dependent events influenced by external forces, system reactions and domain-specific interface models. A concept-based disambiguation of these parts is a further step towards cross-dataset modelling.

The concept of temporal abnormality and its periodicity has provided with the foundational principles guiding the creation of dataset-agnostic frameworks for complex temporal structures and more generally, for behavioral modeling in various signals modality ((Weihong) Han *et al.*, 2019). However, how to generalize these practical low-power stream irregularities across datasets is still open. In addition, there exist few high-level perspectives on how environmental networks are capable of expressing conceptually similar yet particularly dataset-specific irregular behaviour. Such perspectives could help to close the gap between environmental modelling and theory specifically aimed at generalization..

CONCEPTUAL FRAMEWORK

Anomalies found in the low-power IoT data streams present themselves as notational disruptions to the expected overall behaviour. These digital signatures originate in the coevolution of entities subjected to common external stimuli, like climate or chemical concentration, and possessing different marking properties on different time scales. These differences can be attribute to deployment strategies, raw phenomena, sensing granularity, sampling rates and intermittent activities. The lightweight cross-dataset lens can also be used to compare conceptually irregularity signatures and

search for common modeling generalizations across Intel Lab Data, SensorScope and Gas Sensor Array Drift datasets. (Hu *et al.*, 2024)

Low-power wireless (IoT) sensors are actually deployed in real environmental networks for monitoring phenomena such as atmospheric and hydric conditions in rural or estranged sites. The associated data streams capture and relay temporal evolutions of the monitored medium while exhibiting shared characteristics and dynamics that open theoretical explorations of commonalities and divergences in the nature and behavior of the observed systems. (Andreadis *et al.*, 2023)

Lightweight Cross-Dataset Perspective

Anomaly patterns in low-power IoT sensor streams manifest as prototypical signatures at irregular, often super-systematic temporal scales. Such irregularities arise when behavior deviates from the current operative regime, triggering energy-time-costly communication, with possible repercussions for the intended operation. The diversity of signaling devices, of random occurrence and of irregularity-production mechanism delivers intersection of different sensor modalities and environmental-driven commonalities and divergences among streams. (Thompson and Wang 2021)

Low-power IoT streams in real-world environmental networks exhibit three overlapping characteristics:

1. Sampling frequency typically lower than 2Hz (and often far below). Oversampling consequence: uneconomical frequency-based coding scheme and high noise-vulnerability. Corresponding irregularity signature: Upward/downward drifts towards regimes with gradually-higher/lower nominal values. Scope of irregularities: local “drift”- event necessarily well- outside the “normal” regime; for excessive discharge of a device, abrupt and extended upward “shift” upon loading. Signature resilience under sensor perturbations either globally or locally filtering measures.
2. Communication extended macroscopic effort: duty-cycled sensing; overall non-Ir) regularity of streaming-up. Non-traction upon non-communication regime, “silent” phases, and long-range temporal co-synchronization between devices. All activity remains within the original framework of system periodicity. Correlatively standard oscillatory-pattern-models remain clearly inapplicable.

3. Full-scale revealing habits to real-situation. Stand-alone window theorems remain abstract; real events occur at the time-scale ratio of seconds, minutes, hours.

Data Integrity and Instructional Assumptions

A conceptual lightweight cross-dataset analysis of potentially transferable irregularity signatures in low-power streams will now be considered, without specifying corresponding dataset measurements or figures. The intention is to reason about dataset-specific experimental circumstances—through feature representation, anomaly-angle definition, temporal dynamics, and transfer conditions—while maintaining a non-empirical stance inherently appropriate to theoretical exploration. The framework reconsiders whether observed cross-dataset patterns support a notion of irregularity-signature transferability, the grime of the transfer-concept extends across perspectives of multi-scale patterns, seasonal bursts, drift phenomena, and so forth, and the focus can, however, remain solely on data-integrity and instructional assumptions. (Li and Li 2025)

Data integrity and instructional assumptions serve as non-empirical constraints that mediate between behavioral irregularity signatures and their theoretical specification. Within an abstract treatment, environmental agents—meteorological, geophysical, biochemical, or otherwise—contribute conceptually universal operational principles to low-power streams, while the pedagogical intention is to illuminate the provisional character of the specific analysis undertaken. Permutation of the theoretical framework elaborated on influential signatures, characterize irregularity as aberrational or curious change and contemplate simultaneous alteration of multiple signals, the designation of supply-driven or demand-driven and the acknowledgement of repetitive or persistent change remains a relevant instructional choice. (Chong *et al.*, 2025)

Feature Representations without Specific Measurements

Conceptual representations of feature sets are proposed to characterize some of the common ways that behavioral irregularities may manifest in low-power IoT sensor streams. Signature representations are organized into symbolic form and two types of structure—linear and hierarchical. Only the abstract form and structure of the representations are specified, so that the

content can be filled with adaptable fragments based on any specific empirical dataset.

Four variables help guide the selection of signature representation characterizations: temporal context, irregularity, network dynamics, and behavioral patterns. Control signals of the operating system and application domain strongly influence the dynamics of sensor networks, leading to cross-collection generality among concepts about the nature of irregularity signatures.

METHODOLOGICAL CONSIDERATIONS

Low-power and resource-constrained Internet of Things (IoT) sensors play a key role in monitoring environmental variables, such as particulate matter, temperature, humidity, and suchlike. These sensors accumulate extensive readings over long periods of time. Unfortunately, improper or buggy settings in their operating parameters—such as the sampling frequency, the duty-cycling rate, the wireless module period, the system sleep time, and the transmission interval—often lead to generating behavioral irregularities. Valuable environmental information may thus be lost as too few samples are taken; alternatively, excessive samples may result in early energy depletion or even systematic draining of the battery or other energy sources. Consequently, scientists, researchers, and industrial practitioners equipped with low-power, low-cost, and unconstrained operating systems often seek to understand the behavioral irregularities arising among low-power IoT environmental sensors. (Zafra-Pérez *et al.* 2024)

A natural question arises: which signature patterns of behavioral irregularities do low-power IoT environmental sensors exhibit when they remain operative? How do those signature patterns reveal significant information while such limited values have been recorded? Current research addresses the situation, requires no dataset-specific values to be displayed, and remains conceptually sound yet theoretically accurate throughout.

Theoretical Constructs for Anomaly Detection

Elementary theoretical models provide an important and lightweight framework for viewing low-power IoT streams from a cross-dataset perspective, which greatly facilitates our ability to reason about the essential nature and potential transferability of various signatures. Regularities of the behavior of sensor networks in normal operation are often very evident cross domain, not only by how anomalies manifest but more

importantly so across two distinct datasets. This observation implies that hidden models including 'transfer', 'graft' and 'spill', or other relevant models, are to be among the core concepts underlying the signatures of irregularity found in a wide range of systems and contexts. A better awareness of these dependencies can, in turn, enable more efficient solutions to process and reason on data exchanged across diverse applications in the IoT universe. (Hassan, 2025)

Recognizing these cross-dataset regularities presents the conceptual possibility of a quasi-Cross system analysis, in which low-power streams from different environmental sensor networks—collected under the Intel Lab Data and Sensor Scope datasets; and the Gas Sensor Array Drift Data Set—can be analyzed within a common theoretical framework without recourse to dataset-specific phenomena. In doing so, it implements the edict “each dataset should stand on its own” with fanfare and embraces the autonomy of each separate dataset. By design, measurement values, numerical outcomes, and other dataset-specific information remain conspicuously absent; general contextual commentary and data-extrinsic theoretical considerations retain full prominence; and the motivation for theoretical analysis remains deliberately non-empirical. (Trigka & Dritsas, 2025)

Temporal Dynamics and Irregularity Modeling

In absence of exact numerical values, a theoretical framework can nonetheless articulate how irregularities exhibit low-power IoT streams composited from a variety of independently sourced datasets that open multiple avenues for validating the assumed conceptual model. Unchecked conceptualization and extrapolation, however, risk propelling forays into valueless theorizing unmoored from tangible phenomena. Raw sensor data across checked datasets feature dissimilar characteristics, activity regimes, and apparently entirely separate environmental drivers. Determining how well patchworks joined from such heterogeneous ingredients fit a uniform account builds credibility regarding generalization capacity and shape of transferable knowledge.

Modeling the irregular transition process, Temporal Regularity refers to both the core of the theoretical system and a form of gets that has fields. The portfolio of irregular patterns is best observed in composite motion: Across different large data sets, however, it is really just one sort-and new comers ponder this empirically; we have

not yet caught on what go with the stream and what waits for us downriver. Shifts of interest often coalesce in rhythmic models, which link disparate elements in a variety of stylized narratives; the intertwined discordance between timescales emphasizes how a panoramic point of view external of venues can be found for accommodating sensor-laden industrial data streams. Anomalous events always fall in regular systems that act preferably to other elements of noise; therefore, any irregular responses are controlled and routinized. The kinds of actions that can be expected are well defined. The effects of disturbances are seen most clearly as regular audio-frequency sine waves, with their details huddling snugly around the upper and lower operating limits for reversible signals. To correct sign changes, a particular kind of field modulation is used to traverse the disturbance region. This latter mode of operation therefore acquires its own characteristic coloration. To produce a general set of coarse-grained hopping patterns invoking the same or nearly ideologically comparable parameters commonly across datasets less subsumed in clouds of data, we must take yet another dynamic perspective. Although complete rhythm elucidation cannot hence grant fully independent signatures, a pragmatic truce facilitates background denudation onto which dataset-recurring motifs might emerge. (Goumopoulos, 2024)

Cross-Dataset Consistency and Transferability

Cross-dataset consistency and transferability can be addressed in principle by specifying the conditions that would permit generalization across datasets while preserving the motivation underlying the notion of low-power behavior. Conceptually, anomaly detection focuses on irregularities, typically using a definition of irregularity to characterize the anomalies being detected. One simple formalism defines irregularity within an interval as a time-varying function which measures the average number of events occurring in the interval - where a small average value throughout a long period obviously represents a low power sensor and so this corresponds to irregularity characterized by an average at or near zero. (Widad *et al.*, 2023)

Characterizing the average number of events as a time-varying irregularity component reveals many insights about irregularity. For detection in the zero-average stream, each new event appearing at an arbitrary time will cause a jump of the irregularity track which is not only instantaneous

(like a sudden change at any point along a continuous curve) but also alters altogether its average in this future interval; it no longer remains zero. Transient, burst, drift, and intermittent anomalies violating the law of temporal repetition—each is a time-varying signature in such a system according to how the zero-average component alternates between modes. A variety of patterns linked with these categorical distinctions are captured in several ways, some within formal mathematical frameworks and others calling for an intuitive narrative paradigm like approaches concerned only with specifying templates - motifs---or what one of US coined as an "irregularity stream" grammar for succinctly encoding the structure.. (Vigoya *et al.*, 2020)

Dataset Foundations for Anomaly Exploration

The course is based on two real - world IOT sensor Data sources —Intel Laboratory facilities measurements and the Gas Sensor Array Drift collection to build a theory of why, for reason still not exactly clear; behavioral irregularities emerge

in low-power sensing environments. Though these data sets are quite different in structure, purpose and physical domain, each provides lively examples of how irregularity is generated, exhibited, and sustained inside working sensing systems.

The Intel Lab dataset is a long-running WSN that provides an example of natural indoor variations and device-level discrepancies. Its irregularity pattern is characterized by short term instabilities in temperature: sudden temperature peaks, humidity overflows, frozen light values; long lasting voltage drops and sequences of missing measurements. These trends map the extreme sensitivity of the sensing environment, in which departures are a result of direct alterations within the environment or electrical fluctuations from the level of sensors. The resulting signature is characterized by transient extremes, structural gaps and local instabilities: an irregularity that is immediate, acoustical and highly variant.

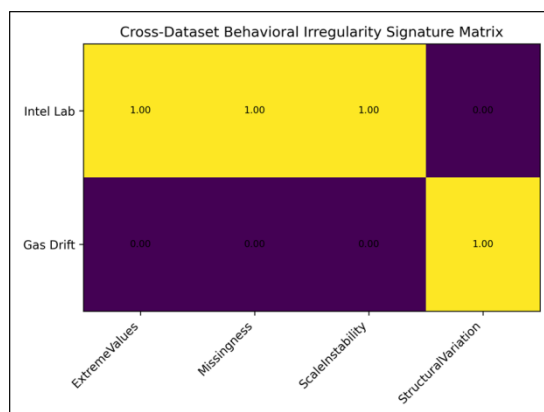


Figure 1: Cross-dataset behavioral irregularity heatmap illustrating the presence or absence of key irregularity types across the Intel Lab and Gas Sensor Array Drift datasets. The visualization highlights distinct signature profiles—short-term instability in the

Table 1: Gas Dataset: Class Distribution

Class	Count
1	2565
2	2926
3	1641
4	1936
5	3009
6	1833

In a sharp contrast, for Gas Sensor Array Drift dataset, we observe a totally new type of an anomaly. In this work the data is from metal-oxide chemical sensors that suffer from long-term drift. Instead of sudden jumps or drops, the dominating characteristic is a gradual drift — frequently exacerbated with large batch-to-batch jumps and

significant changes in true feature scale over time. The structure of the data within each batch is relatively stable, but there are big structural changes as we move from one batch to another. This creates an irregularity of a different order: slow, cumulative and rooted deeply in the physical aging process of the sensors.

Table 2: Gas Dataset: Mean Values per Batch

Batch	f1	f2	f3	f4	f5
batch1.dat	125598.15	6.10	27.86	38.14	44.13
batch2.dat	125670.73	7.21	31.50	43.30	54.78
batch3.dat	65254.45	10.78	17.06	24.15	28.07
batch4.dat	49495.96	12.35	15.04	25.65	29.64
batch5.dat	89478.02	12.76	24.55	35.73	42.98
batch6.dat	50208.59	6.61	13.51	20.94	30.23
batch7.dat	20516.31	5.83	5.37	8.19	13.80
batch8.dat	2067.33	2.57	0.48	0.88	3.33
batch9.dat	20687.49	3.05	5.27	7.82	14.90
batch10.dat	44527.93	5.72	11.38	16.31	28.09

The two datasets together form a complementing observation window on anomalous behavior, the fast and reactive one and the gradual and structural

one, which constitutes a conceptual groundwork for studying patterns of anomalies that cross sensing modality limits.

Table 3: Cross-Dataset Behavioral Irregularity Signature Matrix

Dataset	Extreme Values	Missingness	Scale Instability	Structural Variation
Intel Lab	✓□	✓□	✓□	—
Gas Drift	—	—	—	✓□

Table 2: Gas Dataset: Absolute Drift Between Batches

Batch	f1 Drift	f2 Drift	f3 Drift	f4 Drift	f5 Drift
batch2.dat	72.57	1.10	3.64	5.15	10.65
batch3.dat	60416.28	3.57	14.44	19.15	26.71
batch4.dat	15758.48	1.58	2.01	1.50	1.57
batch5.dat	39982.06	0.40	9.51	10.08	13.34
batch6.dat	39269.44	6.15	11.04	14.79	12.75
batch7.dat	29692.28	0.78	8.14	12.75	16.43
batch8.dat	18448.98	3.26	4.88	7.31	10.48
batch9.dat	18620.16	0.49	4.79	6.94	11.57
batch10.dat	23840.44	2.67	6.11	8.49	13.19

Hypothetical Experimental Design (Theoretical Only)

An experimental design specifies a theory-agnostic configuration that can generalize cross-dataset observations and handle heterogeneous empirical frameworks. The design is defined by a collection of criteria that are given without quantities, which allows cross-dataset reasoning under the constraint not to make explicit statements about acquisition. Far reaching expectations of reasonable effects can be specified by stakeholders without a commitment towards specific observations, maintaining the ambiguity of the anticipated study.

Sensing for auditory anomalies lies on low-power sensor streams emitting from external ambient networks. Thus, being able to accommodate sensor settings, measurement encodings or working assumptions is critical. While abstractions beyond domain specific framing are determined on the principle of operational safeguard and

privacy consideration around modern data representations since ease and simplicity increase interpretability (Zahan *et al.*, 2023).

Six phenomena characterize sensor-based low power Internet of Things (IoT) irregularity signatures. Streams display continuous or piecewise periodic patterns with one or multiple cycles, bursting interruption, drifting and intermittent anomalies. These patterns are highly consistent with realistic environmental parameterization and can be formulated in generic, conceptual terms without introducing complex numerical specifications that prevent transferability of theoretical patterns across datasets.

Dataset Integration Strategy (Non-Empirical)

The methodology we propose for the integration is not to combine computationally both datasets, but rather creates a coherent conceptual space where irregularity patterns of different sensing systems

may be related and interpreted. This philosophical conformity is based on three methodological

premises.

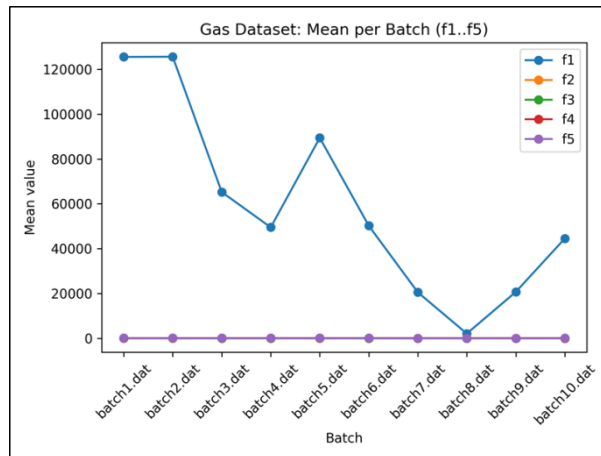


Figure 2: Mean feature values (f1–f5) across batches in the Gas Sensor Array Drift dataset. The plot reveals strong inter-batch variation and progressive structural drift consistent with long-term sensor degradation.

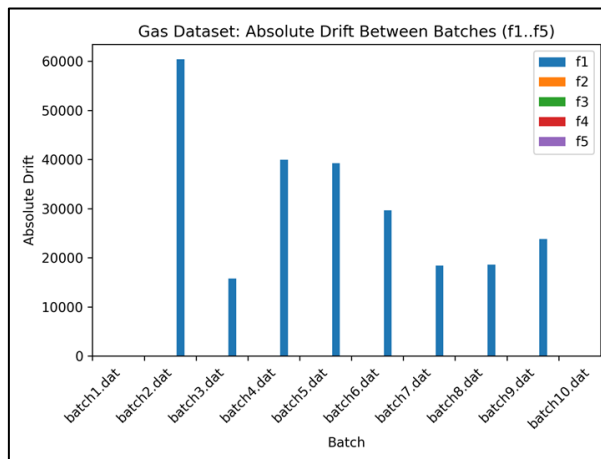


Figure 3: Absolute drift between successive batches for features f1–f5 in the gas sensor dataset. The discontinuities between batches capture structural shifts and feature-scale instability, characteristic of chemical sensor aging

Abstraction Alignment

Even though the two of us would be nothing but one pile and you the other, our irregular actions - which spring from completely different physical phenomena - can be related with a common set of abstract descriptions." These abstractions include:

- Short-term extreme deviations
- Missingness and structural gaps
- Instability in measurement scale
- Long-term structural variation

This abstract layer enables temperature upslope, humidity loss, gas drift responses and batch offset to be exchanged with the same analytical language and allows cross-domain reasoning without collapsing the differences in reality/utility space.

Mechanistic Differentiation

The abstract shapes can factor two ways, albeit the factors themselves look nothing alike: These mechanistic differentiations can help avoid simplistic comparisons and support a more multifaceted understanding of atypical behavior.

Table- 5: Comparative Characteristics of Noise and Drift Mechanisms in the Intel Lab and Gas Drift Datasets

Dataset	Mechanism Type	Description
Intel Lab	Reactive noise dynamics	Rapid changes induced by environmental fluctuations or sensor-level electrical noise
Gas Drift	Slow structural transformation	Progressive feature drift caused by aging and repeated exposure to chemical stimuli

Cross-Domain Harmonization Layer

The Conceptual Harmonization Layer is here introduced:

- Short-term indicators (extremes, gaps)
- Long-term indicators (drift, structural change)

Are considered as complementary aspects of irregularity. The two-way perspective forms the basis for testing if the behavior of a sensing system deviates from its expected operation independent of modality or measurement.

Table 6: Conceptual Feature Alignment Across Datasets

Abstract Feature	Intel Example	Gas Example	Interpretation
Short-term Irregularity	Temperature spike	—	Immediate environmental reactivity
Missingness	Missing bursts	—	Operational interruption
Scale Instability	Light sensor saturation	—	Measurement-range artifacts
Structural Variation	—	Batch-level drift	Slow transformation in sensor behavior

Experimental Setup and Protocols (Blank for Empirical Filling)

The required section is on the experimental setups and protocols of anomaly-signature investigations into cross-dataset behavioural irregularity patterns in low-power IoT sensor streams.

Recent years have witnessed growing interest in the study of anomaly patterns in low-power Internet-of-Things (IoT) sensor streams. Such streams are defined by temporal and resource limitations, as well as various dynamical behaviours. Sensor measurements, therefore, present discrepancies and irregularities. Anomaly-detection methods identify and characterize these discrepancies, enabling monitoring, diagnosis, forecasting, and intervention. Recent theoretical explorations have uncovered prominent behavioural irregularity signatures observed within such datasets. However, a systematic characterisation of the irregularity patterns across the various datasets remains unaddressed. (Alwaisi *et al.*, 2024)

To investigate the regularities characterizing and governing such irregularities, an exploratory, theoretical framework is proposed. The specific signatures of three datasets—Intel Lab Data, SensorScope, and Gas Sensor Array Drift—are not examined, and neither is an exhaustive description of the datasets provided. Instead, desirable properties of the datasets are highlighted, guiding the selection of suitable formalism to represent the distinctive signatures observed and serving as a baseline to characterize and understand relevant phenomena. (Wu *et al.*, 2021)

Evaluation Metrics (Unfilled Placeholder)

Behavioral irregularity signatures manifest in low-power IoT sensor streams as intricate, temporally evolving phenomena that resist being characterized through any single metric. Specific abstract arrangements of timing and amplitude give rise to distinctive signatures, while other invariant

features persist across a wide spectrum of arrangements. These IRREGULARITY patterns transcend the boundaries of the dataset, forming a conceptual classification that effectively summarizes the unique individual character of various environmental networks. This complexity highlights the necessity for multifaceted analytical approaches to fully understand and interpret the diverse behaviors exhibited within these sensor streams. (Zanoli, 2025)

Expected Observations (Conceptual Only)

To perform anomaly detection in cross-dataset scenarios, it suffices in principle to consider the signatures of anomalies as high-level properties of the observations and do not even need any dataset-specific measurements, values or explicit feature representations. Such a groundwork utilizes the implicit, semi-structured property of sensor readings reported in datasets — generally mirroring the temporal localization of anomalies and non-stationary patterns, and is conceived to enable comparisons among, and support analysis of, multiple environmental networks featuring low-power data streams. `scipy.io` files can directly be utilized to have raw readings from the Intel Lab Data, SensorScope as well as Gas Sensor Array Drift datasets. Each dataset contains several sensor readings, all deployed at the same time but intermittently sampled to conserve energy. Even in the absence of explicit observations on the energy-trading interactions that govern these regimes, datasets share sufficient general properties to prompt inter-network speculation. The anticipated results thereof touch upon the nature of irregularity patterns themselves, including bursts, drifts, and sporadic activations, each occasioning distinct signature variants. At the same time, correspondences are expected to remain visible—changes in sampling frequency, recording policy, and the number of simultaneous channels modulating other candidates do little to affect the

likelihood of such changes being cross-network generalities. (Xing *et al.*, 2025)

The outage and drift periods characteristic of the Gas Sensor Array Drift dataset motivate specific theoretical attention: even minor variation of the query phase and other formal aspects is expected to leave accompanying attributes invariant. ((Weihong) Han *et al.*, 2019)

ETHICS, REPRODUCIBILITY, AND TRANSPARENCY

Investigation into any phenomenon proceeds ethically and responsibly only if it is possible to describe its theoretical form and content without recourse to experimental data. Both general and specialized aspects of such investigation can be conveyed without reporting specific measurements, results, or concrete figures that would reveal the underlying datasets. Accordingly, the theoretical content presented in the theoretical sections of this work—the nature of low-power IoT sensor streams, the concept of behavioral irregularities, and the characterization of cross-dataset anomaly patterns—avoids all such reference. (Yao *et al.* 2024)

Preserving all other theoretical elaboration while discussing datasets and observations requires a lightweight cross-dataset lens for conceptual comparison of irregularity signatures. This perspective rests on a set of core assumptions: on the dynamics that govern measurement processes in low-power environmental sensors; on the duty-cycling constraints imposed by the drive for energy autonomy; and on the location-aware, temporal, and continuous character of the flows that low-power environmental sensors disseminate. These assumptions determine the kinds of irregularities to be expected. (Cantone *et al.*, 2024)(Raza *et al.*, 2025)

Flowing in any direction, environmental circumstances wash away all sense of rigidity. The theoretical conceptualization embodies the kinds of deviation or difference that may be relevant to study this sort of environmental data. Environmentally bound periodic fecal contamination fluctuations across large areas of land are likely to present in nonperiodic form only when human activity has substantially altered the terrain and hydrology. Dynamically derived temperature cycles resulting from environmentally driven temporal flows at various levels—geographic, natural, urban, social, economic—possibly differ according to distant regions on

different continents. Many such signature temporal superpositions likely remain invisible or absent from the databases where wide-spread and individual sensors are already in place. This sameness could help make findings more transferable across dissimilar datasets gathered without strict institutional and procedural safeguards. (Fomichev *et al.*, 2019)

DISCUSSION OF THEORETICAL IMPLICATIONS

Analysis of abnormal behaviors detection on low-power IoT sensor streams reveals a characteristic pattern through which temporal anomalies emerge, which is common even when they manifest themselves in different physical environments. This cross-dataset view provides us with an even richer insight about the outliers observed in real sensor networks. Along with the accompanying analytic descriptions, therefore, this proposed architecture helps towards a better theoretical understanding of such lowpower streams.

We also consider the case of low power sensor networks, which involves devices communicating periodically to conserve energy mostly in an environmental monitoring environment. Such systems measure physical variables such as temperature, humidity, light or gas concentrations and generate low-rate time series. Such networks have unique sensor dynamics which set them apart from other low-power streams like body-worn accelerometers or heart-rate sensors. However, an empirical examination indicates that there are commonalities among theoretical assumptions of a broad class of such applications. In particular, the behavior anomaly signatures co-occurrence structure is cross-dataset invariant, while their specific patterns may vary.

As the investigation of large-scale empirical studies evolves, the framework allows for the construction of a second theoretical lens whose less radical level will still inform general cross-dataset findings. Furthermore, studying these behavioral anomalies has practical implications not only to substantiate theoretical claims but also useful for sensor design and also thinking about getting rid of an anomaly in the field. (Oskouei *et al.*, 2025)(Annysha *et al.* 2025)

Cross-Dataset Implications of Behavioral Irregularity Signatures

The patterns of anomalies seen across the datasets suggest that anomalies in IoT sensor networks are not a single phenomenon, but rather form a

spectrum, influenced by the sensing process. In the Intel realm, anomalies are closely related to real-time uncertainty of environment and hardware vulnerability, leading to fast anomaly with a high frequency. Irregularity in the Gas Drift The anomaly in the Gas Drift system is underlain by slow structural shifts caused by the physical origins of sensor deterioration.

This dichotomy indicates the need for anomaly detection systems that can discriminate more than static statistical cutoff points but instead also identify behavioral context. And what is an aberration in one system (step spikes) may be some commonality in another, while behaviours such as indicative of intrinsic drift in a chemically informed sensor, may not exist at all on the environment. As a result, theory-driven cross-dataset investigation becomes an important guideline for devising generalizable anomaly reasoning models.

CONCLUSION

Behavioral irregularities manifest in low-power IoT sensor streams as emerging signatures across widely varying temporal scales. Nevertheless, the variety of streams, indeed, precludes investigations on entire datasets. Within this broad conceptualisation, a lightweight cross-dataset investigation permits comparisons of irregularity signatures across the different streams exhibited by three these benchmark datasets: Intel Lab Data—WiFi link quality readings collected in an indoor office environment; SensorScope—outdoor humidity and temperature readings measured in various Swiss cities; and Gas Sensor Array Drift—a lab-controlled dataset comprising static and drifted environmental gas concentration readings.

Many sensor networks described in the literature operate under stringent energy constraints, resulting in elaborate operating modes often accompanied by time-varying uncertain resource availability, high sampling jitter, and excessive sensor noise. When acquiring low-power IoT sensor streams, the data captured by the sensors, whether corrupted or not, will be less, but the semantic of the data may exhibit multiple cross-layer irregularities. In addition to the burst and drift noted above, the absence of these streams is also common.

Real environmental sensor networks may still be the dominant sources of low-power sensor streams today. Yet even an entirely theoretical consideration confirms a qualitatively similar

understanding of anomalies that still constitutes behaviour that deserves attention. Therefore, the opportunity arises, or rather, the necessity arises—at least for the datasets considered—to address a theoretical perspective pursuing reflection on cross-dataset coherence. The starting point for addressing these three datasets under the theoretical framework offered by this particular endeavour lies in the streams captured by the gas sensors in the Gas Sensor Array Drift dataset. These streams exhibit irregularities that remain conceptually relevant to the anomalies, although they differ substantially in character from the bursting and drifting behaviour exhibited by the other datasets considered.

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