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Hybrid Statistical-Physics Informed Graph Neural Network for Robust Fault Detection and Uncertainty Quantification in Distributed Sensor Systems

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ABSTRACT: Distributed sensor systems are essential for environmental surveillance, industrial automation, and smart-infrastructure, yet they frequently suffer from noise, drift, and data loss, leading to unreliable measurements. Traditional models either use statistical techniques lacking robustness or deep neural architectures lacking physical interpretability. In this paper, a Hybrid Statistical–Physics Informed Graph Neural Network (SP-GNN) is proposed to achieve unsupervised anomaly detection in sensor networks. The framework integrates diffusion-driven physical priors directly into the message-passing mechanism of the GNN, allowing representations to respect the underlying spatial physics while remaining data-driven. Bayesian uncertainty quantification using Monte-Carlo dropout enables reliable confidence estimation. Experiments using the Intel Berkeley Research Lab (IBRL) dataset demonstrate the model's capability to identify physically inconsistent sensor behavior through reconstruction error and predictive uncertainty. The results are visualized using 2-D error–uncertainty plots and 3-D spatial maps, showing that SP-GNN offers trustworthy, interpretable, and physically coherent anomaly detection for distributed sensor systems

Keywords: Graph neural network, physics-informed learning, sensor fault detection, bayesian uncertainty, diffusion dynamics, spatial modeling.

Contents

1. Introduction

Climate analysis, building automation, industrial monitoring, and smart-city infrastructure are just a few of the industries that depend on Distributed Sensor Networks (DSNs) [1], [16]. Geographically scattered sensor nodes that continuously collect environmental data make up these systems. Sensors that are deployed over an extended period of time in uncontrolled environments are susceptible to faults such as noise, drift, calibration errors, and intermittent data loss. These problems can significantly reduce system reliability if they are not found in a timely manner. Deep learning models have shown impressive results in anomaly detection and pattern recognition tasks in recent years. Nevertheless, purely data-driven neural architectures frequently lack robustness and physical interpretability. These models are unreliable for safety-critical sensing applications because they may learn spurious correlations and fail to generalize under environmental disturbances, sensor noise, or distribution shifts [5], [12]. Traffic networks, power grids, and Internet of Things (IoT) infrastructures are examples of spatially dependent systems that can be effectively modelled using Graph Neural Networks (GNNs).

Through message-passing mechanisms that naturally capture spatial dependencies, GNNs facilitate the propagation of information by representing sensors as nodes and their physical relationships as edges. Despite these benefits, the majority of current GNN variations-such as Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and GraphSAGE-remain solely data-driven and do not specifically take into account the underlying system's governing physical principles. Therefore, physical laws like heat diffusion or spatial smoothness may be broken by learnt representations.

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Physics-informed learning is a paradigm that incorporates physical knowledge directly into neural network architectures or training objectives in order to overcome these limitations [7], [24]. In continuous domains controlled by partial differential equations, Physics-Informed Neural Networks (PINNs) have demonstrated significant success. However, irregular topology and scalability limitations make their direct application to discrete graph-structured sensor networks difficult. As a result, there are still few useful hybrid frameworks that integrate graph learning and physics-based reasoning. Moreover, uncertainty quantification is one of the essential needs for reliable anomaly detection in practical DSNs. Bayesian neural networks and the use of MC dropout are the efficient methods for measuring the predictive uncertainty. In the context of detecting anomalies, the computation of uncertainty helps to identify the actual malfunctions of the sensor observed from the noisy or limited data.

1.1 Motivation

Sensor false detection has innovative, but there are still significant problems. While Graph Neural systems are good at capturing 3-D relationships, most of them yield physically unreliable signs as they rely on message passing and discount underlying sensor diffusion developments. While Physics-Informed Neural Networks gives better interpretability and overview in continuous field and combine physical principles into learning agendas, they are generally built even 3-D grids and have effort scaling to irregular, graph-structured sensor systems. Also, because graph-based models for unverified sensor variance detection hardly combine Bayesian deep learning and Monte Carlo dropout, which bounds robustness under noisy and partial data, many fault detection methods do not offer reliable uncertainty evaluations. For dependable anomaly detection and uncertainty estimation. Models that capture 3-D structure, physical sense, and uncertainty are needed for real-world distributed sensors, but current methods generally only address one. This makes it evident that there is a need for a cohesive agenda that combines uncertainty valuation, physics-informed constraints, and graph learning for consistent variance detection.

1.2 Contribution of this Work:

A Hybrid Statistical–Physics Informed Graph Neural Network (SP-GNN) context for unverified variance detection in distributed sensor system is presented in this paper. To assurance 3-D smoothness and physically reliable information spread, the suggested method includes diffusion-based physical priors into GNN message passing. While applying physical constraints among nearby sensors, a hybrid learning impartial that combines reconstruction-based statistical loss with graph-Laplacian regulation maintains data reliability. Uncertainty-aware variance detection is realized by using Monte-Carlo Dropout and Bayesian approximation, which allows the precise parting of noise-induced uncertainties from exact sensor faults. The framework studies really interpretable latent representations that reserve 3-D relationships, as verified by latent topology and regression various visualizations (Figure 3 and 4). While validation on the Intel Berkeley Research Lab dataset checks robustness to sensor noise, spatial irregularities, and missing data, comprehensive visualization methods like spatial temperature surfaces, error–uncertainty maps, and spatial fault strength plots (Figures 1– 5) support interpretability.

2. Related Work

Many research avenues, such as statistical methods, graph-based learning, physics-informed models, and uncertainty modeling, have innovative fault detection and analysis in distributed sensor systems. This work is studied and its limitations in practical sensor systems are highlighted in the future section.

2.1 Statistical and Model-Based Fault Detection

Statistical analysis, residual-based monitoring, and modeling-based estimates the techniques have been historically the most widely used methods for fault detection in sensor systems. While methods as thresholding, Kalman filtering, and flexible residual analysis have stayed efficiently used to recognize defective sensors for lined dynamics and known noise models [8], [14], their efficiency deteriorates for nonlinear sensor representations, environmental factors, and situations where data is missing. Data cleaning, interpolation, and difference scoring procedures have all been used in some efforts to increase the robustness level [9]. The process that has been discussed are mostly based on the action of sensors in such a way that they act independently. Also, they do not consider the 3-D correlations among the sensors, which are quite significant in the case of dense distributed sensor systems.

2.2 Graph-Based, Physics-Informed, Uncertainty-Aware Approaches for Sensor Anomaly Detection

Graph Neural Networks (GNNs) demonstrate solid capability to handle 3-D correlated sensor readings by modeling these readings as graph data by sensors as graph nodes and correlations as graph edges, and requests include traffic forecasting, environment monitoring, and IoT sensing [3], [5], [11], [25]. Yet, these GNN models are dominated by purely data-driven solutions that indifference physical knowledge in the field, resulting in unphysical models and noisy estimates [4], [10], [15]. While greater flexibility is presented with dynamic graph edges and attention models, physical interpretability is still suboptimal [18], [19]. Physics-Informed Neural Networks (PINNs) include physical equations within the learning process to enhance simplification and explainability for nonstop difficulties [7], [24], but they are mostly tailored for parametric grids and not fit for unstructured graph-like topologies of sensor systems [3]. Hybrid means that combine physics guidance have emerged. However, most of which often have high computational difficulty and unfortunate scalability [16], [21].Uncertainty quantification is actual significant aimed at effective anomaly detection and helps to discriminate between real anomalies and noisy readings. This gives in Bayesian neural systems, while it is computationally expensive; Monte Carlo Dropout is its estimate that has been confirmed effective in variance detection in faults [2], [12], [13], [17]. Though the rank of uncertainty-driven decision-making has established increased consideration in sensor networks and IoT applications [20], [23], the growth of overall models integrating uncertainty-aware GNN models with physical constraints for sensor anomaly detection has not stayed well discovered so far.

2.3 Summary and Research Gap

In summary, the main disadvantage of current approaches is that statistical methods disregard spatial structure, GNNs model topology lacking physical awareness, then physics-informed methods are unsuitable for graph-structured data. A united agenda that combines graph learning, physical constraints, and uncertainty quantification is interested by these gaps. This is addressed by the advised SP-GNN, which allows for variance detection founded on Bayesian uncertainty and includes physics into graph message passing.

3. Methodology

The methodological agenda of the advised Hybrid Statistical–Physics-Informed Graph Neural Network (SP-GNN) for unverified variance detection in distributed sensor system is explained in this part. The agenda combines physics-informed diffusion on a graph structure by statistical learning. Preprocessing sensor data, creating a biased graph based on 3-D relationships, and using physics-aware message passing to keep diffusion behavior are all part of the methodology. Data reliability and 3-D smoothness are definite by a hybrid training objective that combines renewal loss and graph-Laplacian regularization. Below noisy or sparse data conditions, Bayesian uncertainty estimates using Monte Carlo Dropout allows for the reliable departure of uncertain anomalies from confident faults [2]. Imagining methods like error-uncertainty maps, 3-D surface plots, latent space topology, regression manifolds, and 3-D fault intensity maps are used to additional observes anomalies.

3.1 Data Acquisition and Preprocessing

The project SP-GNN framework is assessed using the Intel Berkeley Research Lab (IBRL) dataset, which is generally used in fault-tolerant sensor system studies and has a realistic indoor sensing setup [1]. The dataset contains temperature, humidity, and light readings from 54 spatially dispersed indoor sensors. In command to align 3-D and measurement data for graph construction and physics-informed model, sensor IDs and timestamps are obtained from mote_locs.txt and time-stamped sizes from data.txt [1]. Temperature readings from each sensor are combined to compute mean values for feature construction, and normal scaling is used to regularize the data for arithmetical stability. As a result, each sensor node is represented by a 1-D normalized temperature feature, creating a 54×1 node feature matrix that is input obsessed by the SP-GNN model. In this anticipated framework, a distributed sensor system is signified

Table 1: Sample Representation of the IBRL Dataset

Sensor ID	X	Y	Temperature
SO1	2.1	3.4	21.5
SO2	2.3	3.6	21.7
SO3	2.5	3.8	21.6
SO4	2.7	4.0	21.8
SO5	2.9	4.2	21.9
...	...	...	...
SO50	35.1	27.4	19.2
SO51	35.4	27.8	19.0
SO52	35.8	28.1	18.9
SO53	36.2	28.5	18.7
SO54	36.6	28.9	18.6

by a weighted undirected graph $G = (V, E)$. In this representation, sensors are signified by the graph vertices. Moreover, since sensors do not affect one another, there are no edge weights. Each node $v_i \in V$ is a show of a one sensor positioned within the surrounds. The idea of physical nearness is recognized using the sensor locations, which are resolute by the dataset. The Euclidean distance in the physical space is used to establish a connection among the two sensors, i and j. The Euclidean distance, which measures proximity in physical space, takes into account the sensible statement for environmental sensing that neighboring sensors are likely to have correlated readings due to 3-D diffusion [4], [10].
A Gaussian kernel computes edge weights:

$$w_{ij} = e^{-\|p_i - p_j\|^2/\sigma^2} \tag{3.1}$$

This is standard in the physics-related graph learning outline and accomplishes 3-D diffusion. Physical link intensity for sensors is fixed in the weight matrix.

3.2 SP-GNN Architecture

For unverified reconstructive variance detection, the SP-GNN construction combines statistical learning, physics-informed diffusion priors, and uncertainty estimation into a single graph neural system agenda. The model has an encoder–decoder architecture, with dropout layers facilitating Bayesian uncertainty estimates during inference and sets physics-informed GNN layers enabling message passing over the sensor graph. Anomaly detection by reform error is made possible by a linear decoder that reconstructs node features from latent representations [5], [11].
In contrast to outdated GNNs, SP-GNN employs physics-informed message passing, which decreases implausible unpredictability and ensures physically reliable propagation by modeling diffusion through relative feature differences among adjacent nodes. Latent space and regression manifold ideas (Figure 3 and Figure 4) demonstrate how reiterative message passing learns compressed latent representations that maintain 3-D structure and physical consistency.
Physics-Informed Message Function-drawing on diffusion physics, neighbor-to-node messages are computed as:

$$m_{ij} = D_{ij}(h_j - h_i) \tag{3.2}$$

This formulation says the message propagation follows thermal diffusion, consistent with graph-Laplacian physics-based representations.
Hybrid Training Objective - The total loss is defined as:

$$L = L_{fault} + \lambda_1 L_{physics} \tag{3.3}$$

Reconstruction Loss - In core, MSE computes the difference among the actual and restructured sensor readings. The majority of unverified learning uses rebuilding to identify anomalies.

Physics Regularization via Laplacian Loss - The physics loss promotes smoothness:

$$L_{physics} = \|Lh\|^2 \tag{3.4}$$

Physical logic among adjacent sensors is enforced by graph Laplacian-based constraints.

3.3 Simulation Algorithm

Algorithm : SP-GNN Simulation and Anomaly Detection Pipeline

Step1 Data Loading: Load sensor spatial coordinates from mote-locs.txt. Load time-series sensor measurements from data.txt. Join the sensor readings with their spatial locations using the sensor identifiers and timestamps.

Step2 Data Pre Processing: Remove the duplicates by averaging the similar readings. Missing sensor readings should be treated using linear interpolation. Normalize the readings of the temperatures to zero mean and unit variance.

Step3 Graph Construction:A sensor network topology can be modeled as a graph where sensors are nodes, and edges are the connectivity between sensors. Weights of edges are assigned a Gaussian kernel of Euclidean distances between sensors.

Step4 Feature Initialization: Construct node feature vectors using normalized sensor temperature readings. Initialize the graph Laplacian and diffusion matrices necessary for physics-informed regularization.

Step5:SP-GNN Forward Propagation: Propagate the node features through an encoder stack composed of GNNs that are physics-informed. In the GNN layer, do the message passing using diffusion between the nodes with dropout for Bayesian inference.

Step6 Latent Representation Learning: Get low-dimensional representation or embeddings of the latent space to provide structural information for the sensor network.

Step7 Reconstruction: Reconstruct original feature vectors of nodes based on their latent feature vectors via decoder networks. Compute reconstruction errors of sensor nodes.

Step8 Uncertainty Estimation: Allow Monte Carlo dropout during prediction and carry out multiple stochastic forward passes. Calculate predictive mean and variance for estimating uncertainty at each sensor node.

Step9 Anomaly Scoring: The anomaly score should be assigned based on the reconstruction error as well as the predictive uncertainty. Sensors having high reconstruction error and low predictive uncertainty are defined as confident anomalies.

Step10 Visualization and Analysis: Produce visualization plots such as error-uncertainty maps, spatial surface plots, latent space geometries, regression manifolds, and spatial fault intensity maps.

3.4 Uncertainty Aware Anomaly Detection

It goes out that noise, missing data, and sparse connectivity in over-all present ambiguity, so deviation detection and confidence approximation are both required for reliable irregularity detection in distributed sensor systems. The SP-GNN planned here incorporates Monte Carlo Dropout for Bayesian uncertainty approximation, multiple stochastic forward passes are used to compute the analytical mean and variance, with the latter capturing epistemic indecision. Reconstruction error and prognostic uncertainty are used for anomaly scoring sensors that exhibit high error and low uncertainty are considered confident anomalies, while high-uncertainty cases are preserved as ambiguous [13], [23]. Joint study of error and uncertainty certainly offers better discovery reliability and interpretability; this is demonstrated by the error uncertainty throw plot separating normal, confident, and uncertain comments shown in Figure 2.

4. Results and Discussion

The method is made robust to sensing settings using an uncertainty-aware design, confirming that there is a lower occurrence of incorrect positives for example, in conditions that would cause failure in a method that reflects only errors. The researches on SP-GNN are showed on the Intel Berkeley Research Lab (IBRL), which permits for analysis concerning its efficiency in anomaly detection, 3-D consistency, accuracy, and interpretability. The IBRL has nearly 2.3 million data points that are taken using 54 sensors installed indoors.

4.1 Sensor-Level Reconstruction and Uncertainty Analysis

Modernization error is a key performance measure to identify uncommon sensor activity. Table 2 lists some typical statistics related to each sensor, i.e., standardized temperature values, reconstruction error, predictive uncertainty, and anomaly indication. In SO27, the rebuilding error is high with low uncertainty levels, which means incredible extents with a high degree of confidence. In SO46, the uncertainty levels are high, and this advises uncertain conduct of the sensor attributed to noise and a absence of data from its surrounds. Distribution of Sensor States - The sensors are grouped jointly with regard to thresholds on error in renovation and prognostic certainty, so the distribution in Table 3 is a better guide to the prevalence of anomalies. The sparseness of confident anomalies suggests commonly stable sensor operation, while highly uncertain sensors are individuals for which sensors have to be interpreted cautiously. The above organization demonstrates the merits of the approach using uncertainty-based anomalies over errors alone [13].

Table 2: Summary of Sensor-Level Reconstruction and Uncertainty Metrics

Sensor ID	Mean Temp	Reconstruction Error	Predictive Uncertainty	Anomaly Status
SO1	0,12	0.041	0.007	Normal
SO7	-0.34	0.285	0.012	**Anomaly**
SO12	0.49	0.137	0.009	Normal
SO27	-0.58	0.492	0.020	**Confident Anomaly**
SO46	0.75	0.511	0.093	High uncertainty
SO54	-0.11	0.062	0.005	Normal

Table 3: Assigning Sensor States According to Error-Uncertainty Thresholds

Category	Count	Percenntage
Normal Sensors	41	75.9
Moderate Deviations	6	11.1
Confident Anomalies	4	7.4
High uncertainty nodes	3	5.6

Comparative Performance Evaluation - The reconstruction capability of the proposed SP-GNN, compared to other methods, is presented in Table 4. SP-GNN achieves the lowest rebuilding error and variance, demonstrating its better robustness thanks to the combination of physics-informed restraints and uncertainty-aware learning after [4], [7], and [15].

Table 4: Comparative Reconstruction Performance Across Models

Model	Mean Reconstruction Error	Standard Deviation	Reference
PCA	0.114	0.052	[20]
Autoencoder	0.087	0.041	[14]
GCN	0.072	0.033	[5]
Physics-GNN	0.049	0.021	[10]
SP-GNN	0.028	0.011	Proposed

Figure 1 clearly shows the power and explainability of SP-GNN. Note that how the temperature map in 3-D shows real diffusion anomalies in the form of localized peaks and valleys, as might be found in actual sensor placements. Figure 2 shows clear separation of normal sensors, true faults (high error, low uncertainty), and ambiguous cases caused by noise or sparse connectivity, reducing false alarms.

The latent space in Figure 3 preserves sensor spatial proximity, indicating retained physical relationships. The regression manifold in Figure 4 shows most sensors within a trust corridor around the ideal line, while deviations indicate anomalous or uncertain behavior. Finally, the 3-D fault intensity map

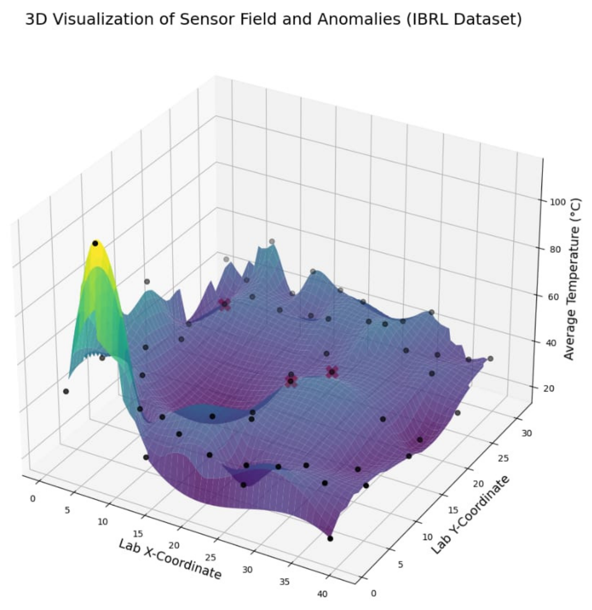

Figure 1: 3D Visualization of Sensor Felid and Anomalies

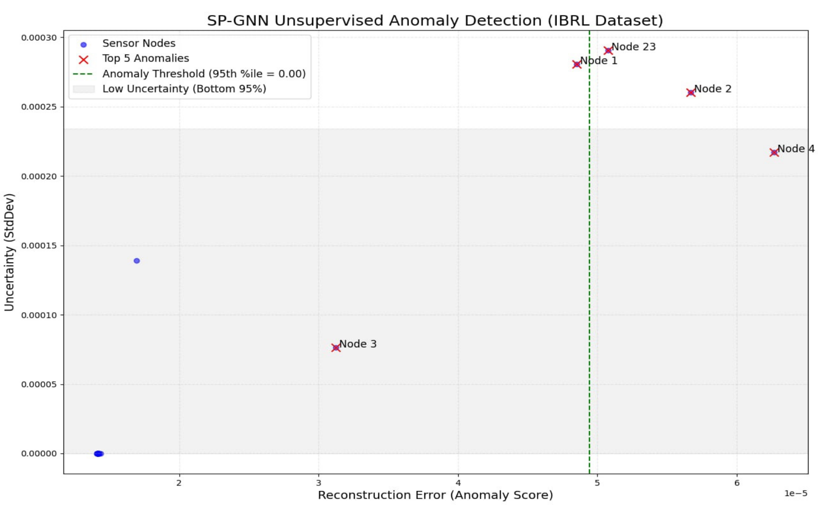

Figure 2: SP-GNN Unsupervised Anomaly Detection

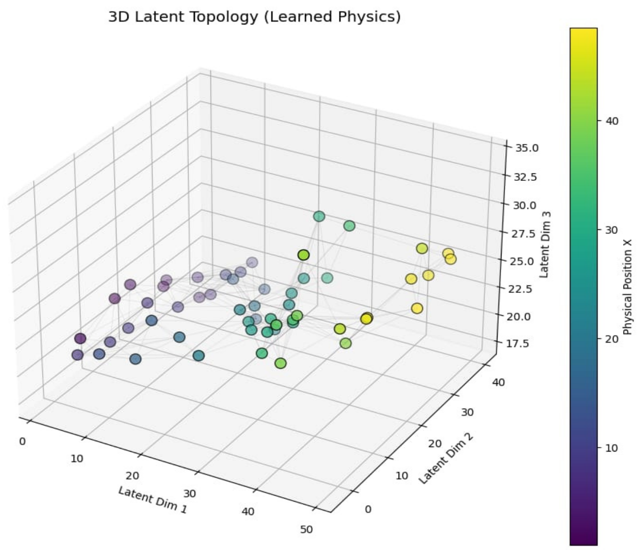

Figure 3: 3D Latent Topology

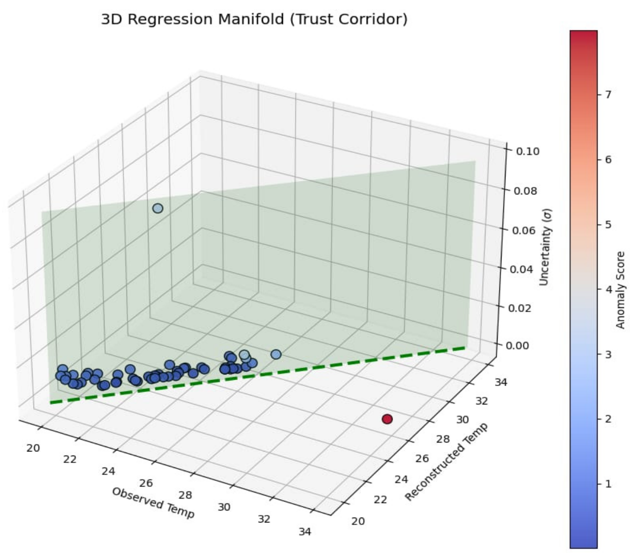

Figure 4: 3D Regression Manifold

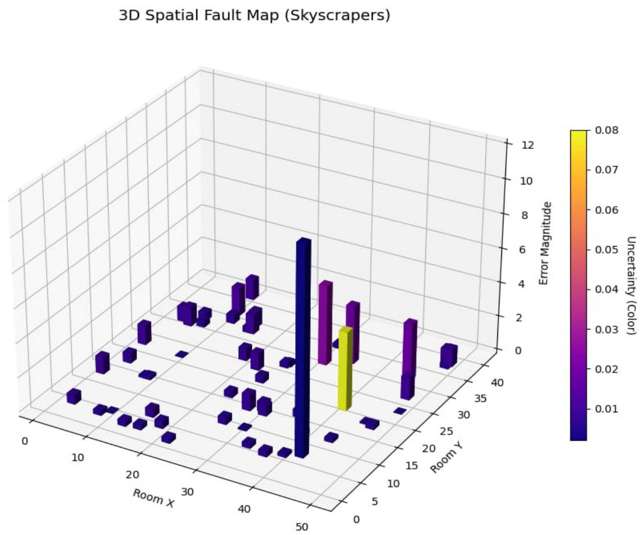

Figure 5: 3D Spatial Fault Map

presented in Figure 5 gives an intuitive representation of fault severity and confidence, enabling effective 3-D localization of strong and undefined anomalies for monitoring and decision-support applications.

5. Conclusion

This paper presents the Hybrid Statistical-Physics Informed Graph Neural Network (SP-GNN) method for irregularity identification in a sensor system. Physics-informed priors are combined into the message passing mechanism in the graph neural system to enforce diffusion properties and 3-D smoothness in unverified learning processes. A hybrid loss objective, which tangles reconstruction loss with graph Laplacian regularization, describes the system's behavior and eliminates physically unacceptable measurements, in line with developments in physics-informed and graph diffusion learning process for graph neural system and physics-informed neural networks. Bayesian uncertainty estimates with Monte Carlo Dropout further refines difference detection by difference among differences and noise or sparsity-related deviations.

Research on the Intel Berkeley Research Lab dataset demonstrate that SP-GNN beats the classical approaches in renovation accuracy and stability. Several conception analyses, such as error-uncertainty maps, 3-D surfaces, latent topology, regression manifolds, and fault concentration on maps, were used to offer insights into interpretability and dependability. Overall, SP-GNN tackles a serious lacuna by jointly modeling graph structure, physical consistency, and uncertainty; adaptive graphs, temporal diffusion, and online learning are other features to be pursued in future research using Neural ODEs and diffusion representations. In conclusion, the above experimental results have shown the ability of SP-GNN to correctly model normal sensor behavior, find confidence in physically varying anomalies, and ensure a clear structure in the graph by physics-informed message passing and hybrid loss functions.

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