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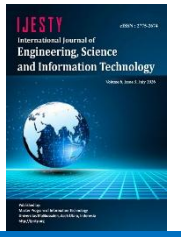


# Physics-Informed Graph Neural Network for Industrial Process Monitoring with Limited Sensor Availability

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## Abstract

Reliable operation and decision-making in industrial process monitoring increasingly depend on sensor networks. However, monitoring accuracy can deteriorate when sensor availability is limited by equipment failures, communication interruptions, or deployment constraints, particularly in complex industrial environments. This study proposes a Physics-Informed Graph Neural Network (PI-GNN) framework for industrial process monitoring under incomplete sensor conditions. The proposed approach combines graph-based representation learning, which captures relationships among process variables, with physics-informed constraints derived from mass and energy conservation principles to improve prediction reliability and robustness. The framework was evaluated using Supervisory Control and Data Acquisition (SCADA) data collected from a palm oil mill in Aceh Utara, Indonesia. Sensor unavailability was simulated through random masking at missing-data rates of 20%, 40%, and 60%. Performance was benchmarked against Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), Graph Attention Network (GAT), and Transformer models under identical experimental conditions. The results demonstrate that PI-GNN achieved the strongest prediction performance under moderate sensor loss, with an RMSE of 0.0785 and an MAE of 0.0532. Under severe sensor degradation, represented by a 60% missing-data rate, the proposed framework maintained an RMSE of 0.1297 and outperformed the Transformer baseline. Ablation analysis further demonstrated that the incorporation of physics-informed constraints contributed substantially to model robustness under incomplete sensor conditions. These findings indicate that integrating graph-based learning with domain-specific physical knowledge can provide a reliable approach for industrial process monitoring when sensor availability is constrained. The proposed framework therefore offers a promising foundation for resilient monitoring systems capable of maintaining predictive performance despite progressive sensor degradation and incomplete process observations in industrial environments.

***Keywords***: *Graph Neural Network, Industrial Process Monitoring, Limited Sensor Availability, Physics-Informed Learning, Sensor Masking.*

## 1. Introduction

Industry 4.0 has been shaped substantially by the convergence of smart manufacturing, cyber-physical systems (CPS), and the Industrial Internet of Things (IIoT), which together have reshaped industrial operations by integrating physical assets with digital intelligence. This convergence supports continuous data acquisition, real-time process monitoring, and intelligent decision-making throughout manufacturing systems [1][2]. As industrial processes grow more complex and interconnected, effective monitoring has become indispensable for safeguarding operational safety, maintaining product quality, boosting production efficiency, and reducing unplanned downtime. The widespread rollout of sensors and IIoT infrastructure have, in turn, produced vast quantities of process data, enabling fault diagnosis, anomaly detection, predictive maintenance, and quality control through advanced analytics [4]. Building on this, artificial intelligence (AI) has emerged as a key driver in converting industrial data into actionable insights, helping shift maintenance strategies away from reactive approaches and toward predictive and condition-based alternatives [5].

Despite these advances, practical manufacturing environments often encounter limited sensor availability. As a result, industrial monitoring systems must operate with missing sensors, sparse measurements, and partially observed process states [6]. Such incomplete observations reduce process observability, hinder accurate characterization of system dynamics, delay the early detection of abnormal conditions, and ultimately degrade monitoring reliability. Because deploying redundant sensors is often economically impractical, developing monitoring methods that remain effective under sparse sensing has become an important research priority. Recent studies have therefore explored sparse representations and sparse learning techniques for industrial process monitoring and fault detection under incomplete observations [7][8][9].

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A wide range of data-driven approaches has emerged for industrial process monitoring, spanning from conventional machine learning algorithms to deep learning architectures such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and Transformers. These models can learn complex nonlinear relationships from historical process data and achieve strong predictive performance under normal operating conditions [10]. However, most existing approaches implicitly assume complete, accurate, and continuously available sensor observations during both training and deployment. Under limited sensor availability, missing measurements disrupt feature representation, reduce prediction accuracy, impair generalization across different operating regimes, and increase sensitivity to uncertainty [11][12]. Furthermore, because these methods rely primarily on statistical correlations without explicitly incorporating the underlying physical mechanisms governing industrial processes, their robustness and interpretability remain limited when sensor information is incomplete [13][14]. These limitations indicate that models relying solely on data-driven feature learning are often insufficient to preserve reliable process representations under sparse sensing conditions, thereby motivating the development of graph-based learning approaches capable of exploiting the structural relationships inherent in industrial systems.

As a deep learning paradigm, Graph Neural Networks (GNNs) have recently gained traction in industrial process monitoring, owing to their natural ability to capture the structural dependencies present in industrial systems. Process units and sensors can be represented as graph nodes, whereas material flows, energy transfers, and process interactions define graph edges. This graph-based representation enables GNNs to explicitly model process topology and has been widely adopted for soft sensing, process monitoring, and fault diagnosis by exploiting structural relationships among process variables [15]. Through message-passing mechanisms, GNNs iteratively aggregate information from neighboring nodes to learn representations that capture both local interactions and global structural dependencies, producing richer representations of process dynamics than conventional grid-based architectures [16]. Nevertheless, most existing GNN-based monitoring methods remain predominantly data-driven and therefore rely heavily on high-quality sensor measurements, making their performance susceptible to missing, noisy, or incomplete observations [17]. To improve robustness under sparse sensing conditions, recent studies have incorporated process graph constraints into graph-based soft sensing frameworks, demonstrating improved representation learning and prediction performance under incomplete observations [18].

Physics-informed learning provides a complementary strategy by embedding fundamental physical principles—including conservation laws, mass and energy balances, flow dynamics, and operational constraints—directly into the learning process. Incorporating such prior knowledge improves model robustness, generalization capability, and physical consistency, particularly when process measurements are noisy or limited [19]. Existing physics-informed neural networks have been developed primarily for scientific computing and partial differential equation (PDE)-governed systems, whereas their application to graph-structured industrial monitoring remains relatively limited [20]. More recently, physics-informed graph neural networks have been introduced for engineering process systems, demonstrating the potential of integrating graph representations with physical knowledge to improve learning reliability [21]. In addition, physics-enhanced graph learning has shown promising results for industrial soft sensing by improving prediction reliability beyond purely data-driven GNNs [22].

Several notable research gaps persist despite these advances. Most existing industrial monitoring approaches still assume complete or largely informative sensor observations, which restricts their usefulness in real-world sparse-sensing environments where measurements are often partially unavailable [23]. While graph neural networks are effective at exploiting topological relationships among process variables, most current methods continue to rely predominantly on data-driven learning without fully incorporating first-principles process knowledge to strengthen robustness under incomplete observations. Similarly, physics-informed approaches to date have concentrated mainly on scientific computing and engineering simulations rather than on industrial process monitoring using graph-structured representations. As a result, frameworks capable of jointly leveraging graph representation learning and physical constraints for reliable industrial process monitoring under limited sensor availability remain largely unexplored. To close this gap, the present study proposes a Physics-Informed Graph Neural Network (PI-GNN) framework, which combines graph representation learning with physics-informed constraints derived from process conservation principles. This framework is designed to enhance monitoring robustness and generalization under limited sensor availability, while maintaining consistency with the underlying physical behavior of the predicted process states.

In response to these gaps, this study sets out to develop and evaluate a Physics-Informed Graph Neural Network (PI-GNN) framework for industrial process monitoring under conditions of limited sensor availability, achieved by integrating graph-structured representation learning with fundamental physical process constraints. The proposed framework is built to preserve topological dependencies, enforce physically consistent process representations, and strengthen monitoring robustness when sensor observations are incomplete. Through this combined approach, predictive performance and generalization are expected to improve under sparse-sensing conditions, all while remaining consistent with the underlying physical behavior of industrial processes. Accordingly, this study makes several contributions: introducing a novel PI-GNN architecture purpose-built for incomplete sensor observations; integrating graph topology with physical constraints to strengthen representation learning; conducting a comprehensive performance evaluation against representative graph neural network and deep learning baselines across diverse sparse-sensing scenarios; and validating the framework's effectiveness in industrial process monitoring tasks—including fault detection and anomaly detection—thereby demonstrating its practical applicability in realistic industrial settings.

## 2. Literature Review

As manufacturing systems evolve into highly interconnected and data-intensive environments under the industry 4.0 paradigm, industrial process monitoring has taken on growing importance. Continuous acquisition of process information from distributed production units is made possible through the integration of Supervisory Control and Data Acquisition (SCADA) systems, Industrial Internet of Things (IIoT) technologies, and advanced communication infrastructure. Together, these technologies offer comprehensive visibility into plant operations, laying the groundwork for intelligent monitoring systems that support real-time operational decision-making [24][25]. The growing availability of large-scale process data has further driven the adoption of artificial intelligence and machine learning techniques for monitoring complex industrial systems. Beyond conventional process supervision, modern monitoring systems now incorporate predictive analytics for fault detection, anomaly identification, process diagnosis, and predictive maintenance [26][27][28]. These capabilities support early detection of abnormal operating conditions, helping to reduce unplanned downtime, improve product quality enhancing production efficiency. Recent systematic reviews have consistently demonstrated that intelligent process monitoring improves equipment reliability, reduces maintenance costs, and enhances operational effectiveness across a wide range of industrial sectors [29][30].

Although sensing technologies have advanced considerably, limited sensor availability remains one of the major challenges in industrial process monitoring. Industrial facilities frequently experience incomplete observations due to sensor failures, communication interruptions, inaccessible measurement locations, equipment degradation, or economic constraints that limit sensor deployment, thereby reducing process observability and the quality of data available for monitoring and operational decision-making [31][32]. To address this issue, various approaches have been proposed, including robust process monitoring, data imputation, virtual sensing, soft sensors, and probabilistic reconstruction models. While these methods have improved monitoring performance, many still rely primarily on statistical relationships learned from historical observations and often degrade when missing data become extensive or operating conditions change significantly. Recent advances, including physics-enhanced graph learning, dynamic virtual sensing, and probabilistic soft sensing, have improved robustness under incomplete observations; however, their generalization across varying missing rates and distribution shifts remains limited [33][34]. Consequently, maintaining reliable monitoring performance under sparse sensing conditions continues to be an open challenge for modern industrial systems.

As a deep learning paradigm for modeling industrial systems built on complex relational structures, Graph Neural Networks (GNNs) have proven effective at representing process variables, equipment units, and sensors as graph nodes—unlike conventional neural networks, which assume Euclidean data representations—while material flows, energy transfers, and process interactions are captured as graph edges. Representations that capture both local interactions and global structural dependencies are learned iteratively through message-passing mechanisms, which aggregate information from neighboring nodes [35]. Among the GNN architectures most widely adopted, Graph Convolutional Networks (GCNs) aggregate neighboring node information to learn structural patterns, while Graph Attention Networks (GATs) dynamically weigh the importance of neighboring nodes through attention mechanisms [36][37]. These properties make GNNs well-suited for industrial process monitoring, soft sensing, and fault diagnosis, where the complex relationships among process variables play a critical role [38][39]. Recent studies further show that graph-based models consistently outperform conventional deep learning approaches by explicitly leveraging the topological dependencies inherent in industrial systems, resulting in more accurate and robust fault diagnosis and process monitoring [40].

By embedding first-principles knowledge directly into the learning objective, physics-informed learning strengthens data-driven models. Within industrial process monitoring, this knowledge is typically expressed through physical constraints derived from conservation principles—such as mass and energy balances—which are incorporated into the optimization process either as regularization terms or as probabilistic constraints. Enforcing consistency with established process physics allows physics-informed models to reduce physically implausible predictions and improve reliability under noisy or incomplete observations. Recent work has shown that incorporating physics-based constraints boosts model robustness, improves generalization, and increases monitoring accuracy in industrial applications—particularly when process measurements are sparse or partially unavailable [22][41].

## 3. Methods

### 3.1. Methodological Framework

To address industrial process monitoring under conditions of limited sensor availability, this study puts forward a Physics-Informed Graph Neural Network (PI-GNN) framework, which combines graph neural networks with physics-informed constraints to model process interactions while preserving physical consistency and strengthening monitoring reliability when sensor observations are incomplete [42][43]. As depicted in Figure 1, the overall methodology unfolds across four sequential stages: data preprocessing, graph and physics modeling, PI-GNN training, and performance evaluation. During preprocessing, raw process data is prepared through cleaning, normalization, and sensor masking, the latter used to simulate limited sensor availability. The graph and physics modeling stage then builds graph representations of process variables and embeds physical constraints directly into the learning framework. Following this, the PI-GNN is trained using a composite objective that jointly optimizes prediction accuracy and physical consistency, after which the trained model is evaluated across multiple sensor availability scenarios using representative metrics for process prediction and anomaly detection.

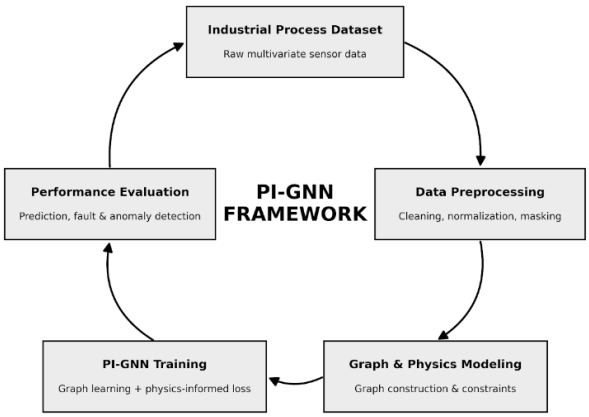


**Fig 1.** The workflow for the proposed Physics-Informed Graph Neural Network (PI-GNN), developed for industrial process monitoring under conditions of limited sensor availability.

### 3.2. Dataset

Evaluation of the developed framework relied on Supervisory Control and Data Acquisition (SCADA) data gathered from a palm oil mill (PKS) in Aceh Utara, Indonesia, spanning roughly three months of operation. This dataset comprises multivariate process measurements collected from key production units—namely the sterilizer, digester, screw press, and boiler—sampled at one-minute intervals. Before model development, standard data cleaning procedures were applied to address missing values and outliers, and Z-score normalization was used to standardize all variables. To assess how robust the framework was under incomplete observations, sensor availability was

deliberately limited through a random sensor-masking strategy applied at missing rates of 20%, 40%, and 60%. This masking-based approach is a well-established method for evaluating the robustness of industrial monitoring and soft-sensing models under incomplete observations [44][45]. Table 1 summarizes the characteristics of the resulting dataset.

**Table 1.** Characteristics of the industrial process dataset.

| Parameter | Description |
|---|---|
| Industrial Facility | Palm Oil Mill (PKS) |
| Location | Aceh Utara, Indonesia |
| Data Source | SCADA System |
| Observation Period | Approximately 3 months |
| Sampling Interval | 1 minute |
| Process Units | Sterilizer, Digester, Screw Press, Boiler |
| Number of Process Variables | 20 *(adjust if necessary)* |
| Total Samples | Approximately 100,000 time steps |
| Data Split | 70% Training, 15% Validation, 15% Testing |
| Sensor Masking Rates | 0%, 20%, 40%, and 60% |

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This study formulates industrial process monitoring as a graph learning problem, representing the production system as a directed graph G = (V, E), where V denotes the set of process variables (nodes) and E represents the physical relationships (edges) among process units. Each sensor measurement corresponds to a node, while edges capture material flow, steam distribution, or pressure interactions within the production process. Through message passing, this graph-based representation allows the network to capture both local and global structural dependencies, thereby strengthening feature representation under conditions of incomplete sensor observations.

In contrast to conventional graph neural networks that depend exclusively on observed data, PI-GNN incorporates physical process knowledge by embedding conservation principles directly into the optimization process. Mass and energy balance constraints are expressed as $R_{mass} = \Sigma \dot{m}in - \Sigma \dot{m}out = 0$ and $R_{energy} = \Sigma(\dot{m}in\,h_{in}) - \Sigma(\dot{m}out\,h_{out}) + Q = 0$, respectively, where $\dot{m}$ denotes the mass flow rate, h is the specific enthalpy, and Q represents the net heat transfer. The model is trained by minimizing a composite objective function, $L = L_{data} + \lambda_{phys} L_{physics}$, in which $L_{data}$ denotes the Mean Squared Error (MSE), $L_{physics}$ penalizes violations of the physical conservation laws, and $\lambda_{phys}$ governs how much the physics-based regularization term contributes during optimization.

## 3.4. Experimental Setup

PI-GNN's performance was benchmarked against several representative sequence-based and graph-based baselines—Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), Graph Attention Network (GAT), and Transformer—using identical training and testing partitions to ensure a fair comparison. Four sensing scenarios were tested: complete observations (0% missing) and random sensor masking at missing rates of 20%, 40%, and 60%, allowing systematic assessment of monitoring performance as sensor unavailability increases. This experimental design aligns with recent studies that employ graph-based architectures and masking strategies for robust sensor fault and anomaly detection [46][47]. Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were used to evaluate prediction accuracy, while Precision, Recall, and F1-score were used to assess anomaly detection performance. To ensure reproducibility and minimize comparative bias, the Adam optimizer was applied with identical hyperparameter settings across all experiments. Table 2 summarizes the full experimental configuration.

**Table 2.** Experimental settings.

| Category | Setting |
|---|---|
| Baseline Models | LSTM, GCN, GAT, Transformer, PI-GNN |
| Optimizer | Adam |
| Learning Rate | 0.001 |
| Batch Size | 64 |
| Number of Epochs | 150 |
| Hidden Dimension | 64 |
| Number of Graph Attention Layers | 2 |
| Physics Loss Weight ($\lambda_{phys}$) | 0.1 |
| Sensor Masking Rates | 0%, 20%, 40%, and 60% |
| Evaluation Metrics | RMSE, MAE, Precision, Recall, and F1-score |

# 4. Results and Discussion

## 4.1. Performance of PI-GNN under Complete Sensor Observations

At the initial evaluation stage, every model tested—Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), Graph Attention Network (GAT), Transformer, and the proposed Physics-Informed Graph Neural Network (PI-GNN)—was trained and evaluated on the complete dataset, with no sensors missing (0% missing rate). To keep conditions consistent across all experimental scenarios, a uniform data-splitting scheme (70% training, 15% validation, and 15% testing), identical hyperparameter settings (learning rate of $10^{-3}$, batch size of 64, and the Adam optimizer), and matching data preprocessing pipelines were applied throughout. This level of standardization ensures that the resulting performance differences reflect purely the intrinsic capabilities of each model architecture.

The training convergence process of the PI-GNN model under complete sensor observations is illustrated in Figure 2. The training loss decreases rapidly during the early stages of optimization before gradually approaching a stable plateau as training progresses. A similar trend is observed for the validation loss, which closely follows the training loss throughout the optimization process without noticeable

fluctuations or divergence. The consistently small gap between the two curves indicates good generalization performance and suggests that the proposed model learns the underlying process relationships effectively without exhibiting signs of overfitting.

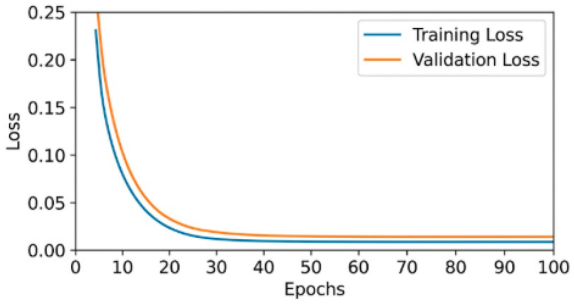


**Fig 2.** Training and validation loss curves of the proposed PI-GNN under complete sensor observations.

Table 3 presents the quantitative prediction results for the process variables. Among all models tested, PI-GNN delivers the strongest performance, with the lowest prediction errors—an RMSE of 0.0785 and an MAE of 0.0532. Relative to the next-best baseline, Transformer (RMSE of 0.1042, MAE of 0.0763), PI-GNN achieves accuracy gains of 24.66% in RMSE and 30.28% in MAE. These results suggest that combining graph structure with physics-informed constraints leads to more precise estimation of industrial process variables when sensor observations are complete.

**Table 3.** Prediction performance of all models under complete sensor observations (0% missing).

| Model | RMSE ↓ | MAE ↓ |
|---|---|---|
| LSTM | 0.1482 | 0.1125 |
| GCN | 0.1295 | 0.0981 |
| GAT | 0.1168 | 0.0874 |
| Transformer | 0.1042 | 0.0763 |
| PI-GNN | 0.0785 | 0.0532 |

The superior performance of PI-GNN under full sensor availability originates from its underlying modeling approach. By leveraging a graph structure, PI-GNN can explicitly represent the spatial relationships and physical topology among process units—something that sequential architectures such as LSTM and Transformer struggle to capture effectively. In addition, the integration of physics-informed constraints based on mass and energy conservation laws functions as a regularization mechanism, steering the optimization toward solutions that remain physically consistent. This guidance ensures that the model's predictions align with the actual dynamic process, thereby enhancing both estimation stability and reliability. These results provide a solid performance baseline for assessing the robustness of the developed framework under limited sensor availability, which is examined in the subsequent subsection.

## 4.2. Performance under Limited Sensor Availability

Following the baseline evaluation under complete sensor observations, all models were further assessed under limited sensor availability by introducing missing sensor observations at rates of 20%, 40%, and 60% during the testing phase. These scenarios were designed to simulate realistic industrial conditions caused by sensor failures, communication interruptions, inaccessible measurement points, or cost-driven sparse sensor deployment. The primary objective of this experiment is to examine the robustness of each model in preserving prediction accuracy as the amount of available sensor information progressively decreases.

Quantitative results under different missing sensor rates are presented in Table 4. As the proportion of missing observations increases, all models exhibit a gradual rise in both RMSE and MAE, confirming that incomplete measurements negatively affect prediction performance. However, the extent of performance degradation varies substantially across architectures. LSTM shows the most severe increase in error, followed by GCN, GAT, and Transformer. In contrast, PI-GNN consistently records the lowest RMSE and MAE values at every missing rate, demonstrating markedly stronger robustness under incomplete sensor observations.

**Table 4.** Prediction performance of all models under different missing sensor rates

| Missing Rate | Model | RMSE ↓ | MAE ↓ |
|---|---|---|---|
| 20% | LSTM | 0.1814 | 0.1397 |
| | GCN | 0.1532 | 0.1184 |
| | GAT | 0.1398 | 0.1063 |
| | Transformer | 0.1275 | 0.0938 |
| | PI-GNN | 0.0914 | 0.0658 |
| 40% | LSTM | 0.2279 | 0.1736 |
| | GCN | 0.1885 | 0.1447 |
| | GAT | 0.1703 | 0.1315 |
| | Transformer | 0.1546 | 0.1178 |
| | PI-GNN | 0.1082 | 0.0793 |
| 60% | LSTM | 0.2968 | 0.2214 |
| | GCN | 0.2446 | 0.1862 |
| | GAT | 0.2218 | 0.1694 |
| | Transformer | 0.1985 | 0.1491 |
| | PI-GNN | 0.1297 | 0.0946 |

The variation in prediction performance across different missing sensor rates is further illustrated in Figure 3. All models exhibit a progressive increase in RMSE as the missing sensor rate rises, confirming that reduced sensor availability degrades prediction accuracy. However, the rate of performance degradation differs markedly among the evaluated models. PI-GNN produces the flattest RMSE curve across all missing-rate scenarios, while LSTM shows the steepest rise in prediction error. Graph-based models (GCN and GAT) outperform LSTM by leveraging structural relationships among process variables, and Transformer achieves further improvement through its global feature representation capability. Despite these relative gains, PI-GNN consistently maintains the lowest prediction error under every testing condition.

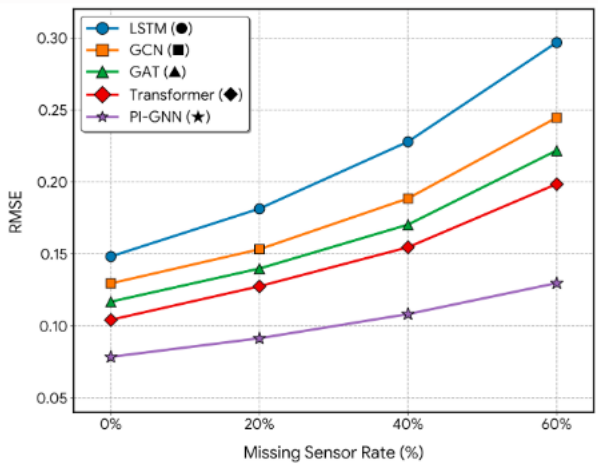


**Fig 3.** RMSE comparison of all evaluated models under different missing sensor rates.

The superior robustness of PI-GNN under limited sensor availability stems from the complementary integration of graph representation learning and physics-informed constraints. The graph structure enables information from the remaining available sensors to propagate through the physical topology of the industrial process, thereby preserving meaningful structural relationships even when portions of the sensor network become unavailable. Concurrently, the embedded physics-informed constraints guide the optimization process toward physically consistent solutions, mitigating the adverse effects of incomplete observations on prediction accuracy. As the missing sensor rate increases from 20% to 60%, PI-GNN records the smallest rise in prediction error among all evaluated models. This result indicates that the proposed framework is substantially more resilient to sparse sensing conditions than conventional deep learning and graph-based approaches. These findings demonstrate that combining physical knowledge with graph-structured learning offers an effective solution for reliable industrial process monitoring under limited sensor availability.

## 4.3. Effect of Physics-Informed Constraints

For a more thorough assessment of the physics-informed component's role, an ablation study compared the complete PI-GNN model against a variant with the physics loss term removed, referred to as PI-GNN (w/o Physics Loss). Both models share identical graph architectures, hyperparameter settings, and training protocols, differing only in whether the physics-informed loss is present. This setup makes it possible to isolate the specific contribution of physics-based constraints to prediction accuracy and robustness across different levels of sensor availability.

The quantitative results of this ablation study are reported in Table 5. Across every missing-sensor scenario, the complete PI-GNN consistently yields lower prediction errors than the variant without physics constraints. With all sensors available (0% missing), PI-GNN attains an RMSE of 0.0785 and an MAE of 0.0532, outperforming PI-GNN (w/o Physics Loss), which records an RMSE of 0.0921 and an MAE of 0.0668. As the proportion of missing sensors climbs from 20% to 60%, the performance gap in favor of the full model holds steady, suggesting that physics-informed constraints continue to enhance accuracy even as sensing conditions become increasingly sparse.

**Table 5.** Ablation study of the proposed PI-GNN with and without physics-informed constraints under different missing sensor rates

| Missing Rate | Model | RMSE ↓ | MAE ↓ |
|---|---|---|---|
| 0% | PI-GNN (w/o Physics Loss) | 0.0921 | 0.0668 |
| | PI-GNN (Full Model) | 0.0785 | 0.0532 |
| 20% | PI-GNN (w/o Physics Loss) | 0.1085 | 0.0797 |
| | PI-GNN (Full Model) | 0.0914 | 0.0658 |
| 40% | PI-GNN (w/o Physics Loss) | 0.1268 | 0.0932 |
| | PI-GNN (Full Model) | 0.1082 | 0.0793 |
| 60% | PI-GNN (w/o Physics Loss) | 0.1483 | 0.1094 |
| | PI-GNN (Full Model) | 0.1297 | 0.0946 |

The effect of the physics-informed constraints on model performance is further illustrated in Figure 4. Both models exhibit increasing RMSE as the missing sensor rate rises, confirming that incomplete sensor observations progressively reduce prediction accuracy. However, the complete PI-GNN consistently maintains lower RMSE values than PI-GNN (w/o Physics Loss) across all testing scenarios. Moreover, the nearly parallel trends observed in Figure 4 indicate that the performance advantage provided by the physics-informed constraints is preserved from complete sensor observations to the most challenging sparse-sensing condition (60% missing rate).

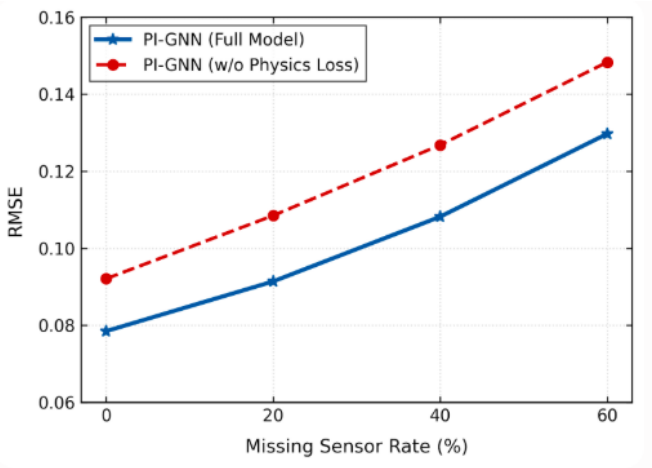


**Fig 4.** Ablation study of the proposed PI-GNN with and without physics-informed constraints under different missing sensor rates.

The improved performance of the complete PI-GNN can be attributed to the complementary integration of graph representation learning and physics-informed constraints. While the graph neural network captures the structural dependencies among industrial process variables, the additional physics loss regularizes the optimization process by enforcing compliance with mass and energy conservation laws. This additional supervision guides the model toward physically consistent representations and reduces its reliance on purely statistical correlations extracted from incomplete observations. Consequently, the complete PI-GNN maintains higher prediction accuracy and exhibits greater robustness than PI-GNN (w/o Physics Loss), particularly under severe sensor loss. These findings confirm that the physics-informed component is a key factor contributing to the reliability of the proposed framework for industrial process monitoring under limited sensor availability.

## 4.4. Discussion

Findings from the experiments show that the proposed Physics-Informed Graph Neural Network (PI-GNN) consistently outperforms conventional deep-learning and graph-based baselines, regardless of whether sensor observations are full or restricted. This improved performance stems from the complementary benefits of graph representation learning and physics-informed constraints. The graph structure allows the model to explicitly encode the topological connections and spatial dependencies among process variables and equipment units [35]. Via message-passing operations, the network gathers information from adjacent nodes, thereby learning representations that reflect both local interactions and broader structural relationships [36][37]. Such structural encoding is particularly advantageous for complex industrial processes, where variable relationships are dictated by process connectivity. In addition, the incorporation of physics-informed constraints strengthens model robustness by ensuring consistency with fundamental process principles, especially when observations are noisy or incomplete [19][41].

Alongside the graph component, physics-informed constraints play a key role in strengthening model robustness. By treating mass and energy conservation principles as soft constraints within the loss function, the optimization process is steered toward solutions that remain physically consistent [19][41]. This regularization lessens the model's reliance on purely data-driven correlations and reduces the likelihood of generating physically implausible predictions, especially under sparse sensing conditions. The ablation study confirms that removing the physics loss term results in a consistent decline in prediction accuracy, with this performance gap widening further as the proportion of missing sensors increases. Taken together, these findings suggest that physical knowledge acts as an effective for

Compared with existing literature on industrial process monitoring, the proposed PI-GNN addresses a key limitation of purely data-driven approaches that struggle under limited sensor availability. While previous graph neural network studies have demonstrated the benefit of modeling process topology for soft sensing and fault diagnosis [15][18], most of them remain primarily data-driven and do not explicitly enforce physical consistency. Conversely, conventional physics-informed neural networks typically operate on Euclidean or sequential representations and do not fully exploit the relational structure inherent in industrial systems [19]. The present work bridges these two research directions by integrating graph-based learning with physics-informed regularization, resulting in improved accuracy and robustness under realistic sparse-sensing scenarios.

From an industrial perspective, the results have practical implications for process monitoring in real manufacturing environments. Sensor failures, communication interruptions, and cost-driven sparse deployment are common challenges in large-scale industrial plants [31][32]. A monitoring framework that maintains reliable performance under such conditions can support more dependable fault detection, soft sensing, and predictive maintenance, ultimately reducing unplanned downtime and improving operational safety [4][5]. The ability of PI-GNN to leverage both structural process knowledge and physical laws makes it particularly suitable for complex industrial systems where complete sensor coverage cannot always be guaranteed.

Although the results are encouraging, several limitations must be recognized. The present study assumes that the process topology used to build the graph is both known and static; in real applications, however, topological alterations or uncertain connectivity may arise. Moreover, the physics-informed constraints applied here are restricted to mass and energy conservation laws; more intricate physical phenomena, such as reaction kinetics or heat-transfer dynamics, have not yet been included. Finally, the evaluation relies on a single industrial process dataset, so additional validation across diverse process types and operating conditions is necessary to thoroughly establish how well the proposed approach generalizes across different settings

## 5. Conclusion

In this work, a Physics-Informed Graph Neural Network (PI-GNN) framework was developed to support industrial process monitoring in conditions of restricted sensor availability. By combining graph-based representation learning with physics-informed constraints based on mass and energy conservation principles, the framework successfully models complex interdependencies among process variables while preserving physical consistency in its predictions. Experiments conducted on SCADA data from a palm oil mill showed that PI-GNN consistently surpassed LSTM, GCN, GAT, and Transformer baselines under both full and partial sensor conditions. Robustness tests involving sensor masking revealed that PI-GNN sustained lower prediction errors even as sensor coverage declined, including highly challenging scenarios with 60% missing observations. In addition, the ablation study verified that the physics-informed component yields further gains in accuracy and reliability relative to a purely graph-based model without physical constraints. Overall, the findings suggest that integrating graph neural networks with domain knowledge offers a promising pathway for building dependable industrial monitoring systems in settings with limited sensor availability. Future research will aim to adapt the framework for real-time implementation, incorporate adaptive sensor selection strategies, and evaluate its performance across a broader range of industrial processes.

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