A Truth Discovery Method for Mobile Crowd Sensing in Mines Based on a Hybrid Bi-LSTM/GRU Network

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***Abstract*—Ensuring safety and operational continuity in underground coal mines requires robust mine monitoring. Traditional methods based on fixed sensors and manual inspections suffer from limited coverage, high cost, and poor real-time performance. Mobile Crowd Sensing (MCS), enabled by miner-carried devices, offers flexible coverage but introduces challenges such as data sparsity, noise, and heterogeneity due to device variability and electromagnetic interference. This article proposes a Bidirectional Long Short-Term Memory/Gated Recurrent Unit-based Truth Discovery (BLGTD) method for mine MCS. The model integrates spatiotemporal sequence modeling with Monte Carlo Dropout-based uncertainty quantification, enabling adaptive fusion of multi-source data. Experimental results show that BLGTD achieves a mean absolute error (MAE) of 0.19 ± 0.01 ppm in CH_4 concentration estimation when 90% of data comes from reliable miners, yielding a 57.8% improvement over traditional weighted averaging. The method demonstrates strong robustness under conditions of data incompleteness, device heterogeneity, and signal interference.**

***Index Terms*—Mobile Crowd Sensing, Truth Discovery, Bi-LSTM/GRU, Mine Monitoring**

I. Introduction

The rapid advancement of mobile communication networks and the widespread adoption of smart devices have established Mobile Crowd Sensing (MCS) as an efficient paradigm for large-scale data collection [1]. By leveraging the mobility and distribution of numerous mobile users and their devices, MCS facilitates extensive, fine-grained sensing tasks, demonstrating considerable potential in applications such as smart cities [2], environmental monitoring [3], and indoor localization [4].

Driven by the expansion of mining operations and advancements in intelligent mining technologies, mine safety monitoring faces new challenges in data collection coverage and quality assurance [5]. Traditional systems combine fixed underground sensors with periodic manual inspections but suffer from limited coverage, high maintenance costs, and measurement errors [6]. MCS, leveraging miners' portable devices, enhances data coverage and flexibility, overcoming some limitations of fixed sensors. However, device heterogeneity and variable miner behavior cause significant fluctuations in data quality. Communication interruptions, sensor malfunctions, and human factors further contribute to data loss and inconsistency, increasing uncertainty. These issues result in noisy, incomplete, and heterogeneous data, hindering the extraction of reliable truth values, which are crucial for improving monitoring effectiveness.

Existing truth discovery methods often rely on techniques like weighted averaging or majority voting [7] to infer reliable values from multi-source data. While effective in some cases, these methods struggle in mining environments with strong temporal dependencies, sparse data, and frequent noise. Recent deep learning advancements, particularly Recurrent Neural Networks (RNNs), have shown promise in modeling sequential data and addressing temporal dependencies [8]. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks excel at capturing both short- and long-term dependencies in time series data [9], [10]. However, LSTM or GRU networks alone cannot fully address data sparsity and heterogeneity in mine safety monitoring. Moreover, many existing methods rely on fixed-weight fusion strategies and lack uncertainty estimation or adaptability to dynamic miner behavior, leading to delayed or inaccurate truth discovery, especially during sudden CH_4 concentration changes that may exceed safety thresholds.

This article proposes a Bidirectional Long Short-Term Memory / Gated Recurrent Unit-based Truth Discovery (BLGTD) method for mobile crowd sensing in underground mines. BLGTD enhances data reliability and completeness by first utilizing sparse, high-quality data from fixed sensors and reliable miners to construct an incomplete observation matrix. A hybrid Bi-LSTM/GRU network is then employed to impute missing data. Monte Carlo (MC) Dropout [11] is used for uncertainty estimation, generating a comprehensive matrix of observed and inferred values. Through iterative truth discovery, the quality of environmental sensing data is significantly improved.

The main contributions of this article are as follows:

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- A novel truth discovery method based on a hybrid Bi-LSTM/GRU network is proposed, effectively addressing data loss and unreliability in mine safety monitoring to improve overall data quality.
- By incorporating MC Dropout, the proposed method quantifies prediction uncertainty and dynamically adjusts truth discovery weights, enabling adaptive fusion with real-world observations to enhance data reliability.

The remainder of this article is organized as follows: Section II reviews related work. Section III introduces the system model and problem formulation. Section IV details the proposed BLGTD method. Section V presents experimental results. Section VI concludes the article.

II. Related Work

MCS has become a promising data acquisition approach to complement traditional fixed sensor-based systems for mine safety monitoring, leveraging mobile users' devices in underground environments. However, mine monitoring faces challenges due to the complexity of conditions and heterogeneous data quality, hindering the extraction of reliable information from diverse sources. Recent advancements in the integration of Internet of Things (IoT), wireless sensor networks, and edge computing have improved monitoring accuracy but remain limited in mine settings.

Traditional truth discovery methods, such as weighted averaging or majority voting, struggle with heterogeneous and noisy data. To address this, Ye *et al.* [12] proposed a probabilistic model based on mean and median checks to eliminate unreliable sources, improving inference accuracy. However, these models lack adaptability to dynamic data. Yang *et al.* [13] introduced the LC-TDC framework, using Deep Matrix Factorization (DMF) for missing data imputation, but the inference error remained high (above 0.85 ppm) in scenarios with over 90% data sparsity. Bai *et al.* [14] proposed a drone-based verification system that enhanced data reliability in open environments, though it failed in underground mines due to positioning errors.

Despite progress, current methods have two main limitations: the lack of cross-validation between fixed sensor data and mobile data, and insufficient uncertainty quantification in deep learning predictions. This article addresses these challenges by constructing a sparse matrix and incorporating cross-validation across heterogeneous sources to improve truth discovery accuracy. Additionally, we integrate MC Dropout with deep learning models to estimate uncertainty, enabling more robust and efficient data fusion in mining environments.

III. System Model

A. Mine-Oriented Mobile Crowd Sensing Architecture

The proposed mine-oriented mobile crowd sensing system supports underground safety monitoring through a collaborative architecture composed of a ground-level Data Processing Center (DPC) and an underground sensing network, as illustrated in Fig. 1. The system enables robust data fusion and dynamic evaluation via four key components:

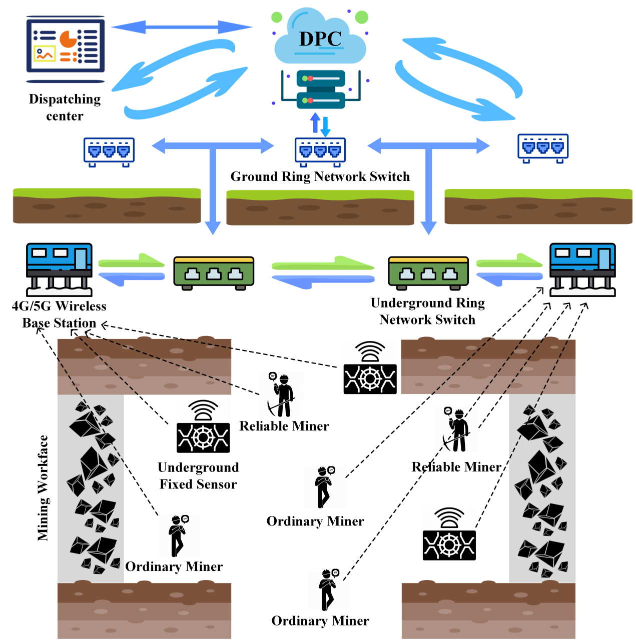


Fig. 1: Mine-Oriented Mobile Crowd Sensing System Model

- **Data Processing Center (DPC)**: Responsible for managing task dispatch, data reception, and storage. It employs a Bi-LSTM/GRU hybrid network for data imputation and utilizes MC Dropout to estimate prediction uncertainty. Data from fixed sensors and reliable miners are fused to create a benchmark dataset for model training and truth inference.
- **Underground Fixed Sensors**: Deployed at key locations to continuously monitor environmental variables (e.g., temperature, humidity, methane, CO, and O_2). Their high accuracy makes them reliable ground truth sources. The restricted coverage imposed by complex mine topologies necessitates the integration of mobile sensing to achieve full-area monitoring.
- **Reliable Miners**: Miners with consistent and accurate sensing behavior. Their data are deemed trustworthy and directly contribute to training and inference.
- **Ordinary Miners**: General miners whose data may contain noise or bias. Their information is refined through deep learning-based imputation and uncertainty quantification.

In the mine, the predefined I fixed monitoring points $P = \{P_1, P_2, \ldots, P_I\}$ are each equipped either with a fixed sensor or designated for mobile miners' data collection. A static spatial encoding $p_i \in \mathbb{R}^k$ denotes the position of monitoring point P_i, forming a spatiotemporal feature vector $f_{(i,t)} = [p_i; t] \in \mathbb{R}^{k+1}$ when combined with time step t. The N fixed sensors record data vectors $a_n(t) \in \mathbb{R}^d$ at each time t, forming sequence $A = \{a_{n,t}\}_{n=1,t=1}^{N,T}$. Additionally, J reliable miners provide data vectors $c_j(t) \in \mathbb{R}^d$, forming sequence $C = \{c_{j,t}\}_{j=1,t=1}^{J,T}$. Ordinary miners $S = \{s_1, \ldots, s_Y\}$ generate observations $x_i(t) \in \mathbb{R}^d \cup \{\mathrm{NaN}\}$ in unmonitored regions, forming sequence $X = \{x_{i,t}\}_{i=1,t=1}^{I,T}$, with $x_i(t) = \text{NaN}$ if no miner covers point P_i at time t.

Data collection occurs in two stages. First, fixed sensors and reliable miners synchronously collect data to form a sparse matrix. Second, the Bi-LSTM/GRU model, trained on this matrix and guided by MC Dropout uncertainty, imputes missing values and verifies ordinary miner data.

Overall, the system supports continuous, fine-grained environmental monitoring in underground mines. By combining deep temporal modeling with uncertainty-aware fusion, it enhances the quality and reliability of crowdsensed data for safety-critical applications.

B. Problem Definition

The goal of truth discovery in mine-oriented mobile crowd sensing is twofold: reconstruct a complete environmental state from sparse multi-source observations, and quantify predictive uncertainty to enable robust data fusion. Given the sparse input $Z(t)$, composed of fixed sensor data $\{a_n(t)\}_{n=1}^{N}$ and reliable miner data $\{c_j(t)\}_{j=1}^{J}$, the system aims to estimate a spatiotemporally complete global truth matrix $\hat{X}$ that satisfies the following optimization objectives.

Definition 1: Temporal Modeling Objective

A Bi-LSTM captures long-range temporal dependencies, while GRU gates enhance local feature adaptation. The learning objective is to minimize the mean absolute error (MAE) between predictions and simulated ground truth:

$$\min_{\Theta} \frac{1}{T} \sum_{t=1}^{T} \|\mu(t) - x^*(t)\|_1 \tag{1}$$

where Θ denotes model parameters, $\mu(t) = \{\mu_i(t)\}_{i=1}^{I}$ is the predicted mean vector, and $x^*(t) = \{x_i^*(t)\}_{i=1}^{I}$ indicates the known complete ground-truth values in the simulation experiments.

Definition 2: Uncertainty Constraint

To avoid overconfident predictions in high-uncertainty regions, MC Dropout is applied. The average uncertainty across time steps is bounded by a threshold:

$$\text{s.t.} \quad \frac{1}{T} \sum_{t=1}^{T} \bar{U}(t) \le \epsilon_U \tag{2}$$

where $\bar{U}(t) = \frac{1}{I}\sum_{i=1}^{I} U_i(t)$ is the mean predictive uncertainty, and ϵ_U is the system-defined threshold.

Definition 3: Safety Constraint

Predicted values must comply with domain-specific safety limits:

$$\mu_i(t) \in [0, C_{\max}], \quad \forall i \in [1, I],\ t \in [1, T] \tag{3}$$

Final Optimization Objective

The overall objective combines accuracy and uncertainty minimization via regularized loss:

$$\min_{\Theta} \quad \frac{1}{T} \sum_{t=1}^{T} \left(\|\mu(t) - x^*(t)\|_1 + \lambda \bar{U}(t)\right)$$

$$\text{s.t.} \quad \mu(t) \in [0, C_{\max}], \quad \forall i, t \tag{4}$$

where λ is a regularization coefficient controlling the trade-off between prediction accuracy and uncertainty suppression. The safety constraint is enforced via a sigmoid activation function in the output layer.

IV. Design and Implementation of BLGTD

The proposed BLGTD method addresses multi-source time-series modeling and truth estimation for underground mobile crowd sensing. Its objective is to verify and complete ordinary miners' submissions by leveraging reliable data from fixed sensors and high-confidence miners.

A. Hybrid Network Architecture

To cope with data heterogeneity, temporal dependence, and incompleteness, we design a hybrid neural architecture combining Bi-LSTM and GRU, as shown in Fig. 2. This structure captures bidirectional dependencies, adapts to miner-specific features, and incorporates MC Dropout for uncertainty quantification.

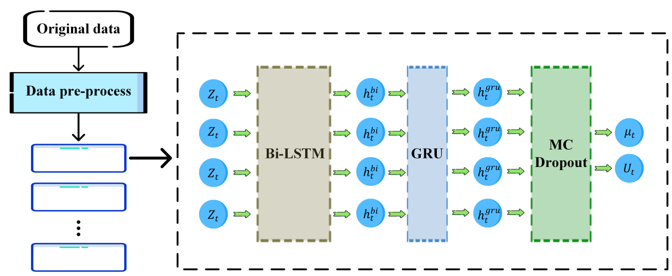


Fig. 2: Architecture of the Bi-LSTM/GRU Hybrid Network

1) Bidirectional Temporal Modeling: Sensor and reliable miner data are concatenated into:

$$Z(t) = [a(t); c(t)] \in \mathbb{R}^{(N+J)\times d} \tag{5}$$

A Bi-LSTM processes the sequence bidirectionally:

$$\overrightarrow{h_t} = \text{BiLSTM}_f(Z(1:t)) \tag{6}$$

$$\overleftarrow{h_t} = \text{BiLSTM}_b(Z(T:t)) \tag{7}$$

$$h_t^{\text{bi}} = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{8}$$

2) Miner Feature Adaptation: The GRU receives input:

$$z_{i,t} = \sigma(W_z[h_{i,t-1}^{\text{gru}}; h_t^{\text{bi}}; f_{i,t}] + b_z) \tag{9}$$

$$r_{i,t} = \sigma(W_r[h_{i,t-1}^{\text{gru}}; h_t^{\text{bi}}; f_{i,t}] + b_r) \tag{10}$$

$$\tilde{h}_{i,t} = \tanh(W_h[r_{i,t} \odot h_{i,t-1}^{\text{gru}}; h_t^{\text{bi}}; f_{i,t}] + b_h) \tag{11}$$

$$h_{i,t}^{\text{gru}} = (1 - z_{i,t}) \odot h_{i,t-1}^{\text{gru}} + z_{i,t} \odot \tilde{h}_{i,t} \tag{12}$$

The output is passed to a fully connected layer:

$$\hat{x}_i(t) = C_{\max} \cdot \sigma(W_o h_{i,t}^{\text{gru}} + b_o) \tag{13}$$

where z_t is the update gate controlling the transmission of historical information, r_t is the reset gate determining the extent of feature forgetting, $\tilde{h}_{(i,t)}$ denotes the candidate hidden state, and $h^{gru}_{(i,t)}$ represents the current hidden state. Additionally, W_z, W_r, W_h, and W_o are trainable weight matrices; b_z, b_r, b_h, and b_o are bias terms; σ indicates the sigmoid activation function; and $\odot$ denotes the Hadamard product.

3) Uncertainty Quantification: With M MC Dropout samples, prediction mean and variance are:

$$\mu_i(t) = \frac{1}{M}\sum_{m=1}^{M} \hat{x}_i^{(m)}(t) \tag{14}$$

$$U_i(t) = \frac{1}{M-1}\sum_{m=1}^{M}\left(\hat{x}_i^{(m)}(t) - \mu_i(t)\right)^2 + \epsilon \tag{15}$$

where $\hat{x}_i^{(m)}(t)$ denotes the predicted value sequence generated during each forward propagation, and $\epsilon = 10^{-6}$ ensures numerical stability.

4) Dynamic Truth Fusion: Compute deviation:

$$\delta_i(t) = \frac{\|x_i(t) - \mu_i(t)\|_2}{\sqrt{U_i(t)}} \tag{16}$$

Weight is derived as:

$$w_i(t) = \frac{\exp(-\delta_i(t))}{\sum_{v=1}^{I}\exp(-\delta_v(t))} \tag{17}$$

Final estimated truth:

$$\hat{X}_i(t) = \begin{cases} w_i(t)x_i(t) + (1 - w_i(t))\mu_i(t), & x_i(t) \neq \text{NaN} \\ \mu_i(t), & x_i(t) = \text{NaN} \end{cases} \tag{18}$$

The global truth estimation matrix is $\hat{X} = \{\hat{X}_{i,t}\}_{i=1,t=1}^{I,T}$.

This design captures the global environmental evolution through bidirectional temporal modeling, adapts to individual miner characteristics via the GRU gating mechanism, and quantifies predictive uncertainty using MC Dropout. As a result, it achieves robust truth discovery under complex electromagnetic interference and data-missing scenarios in coal mine environments.

B. Truth Discovery Process Based on Bi-LSTM/GRU and Uncertainty

The BLGTD algorithm performs temporal modeling, prediction, and uncertainty-aware fusion to estimate reliable ground truth in underground sensing systems. The process is summarized in Algorithm 1.

V. Performance Evaluation

A. Experimental Setup

We evaluate the performance of the proposed BLGTD method on real-world data from a mobile crowd sensing system deployed in an underground coal mine. The goal is to assess its accuracy, robustness, and ability to handle missing and noisy data.

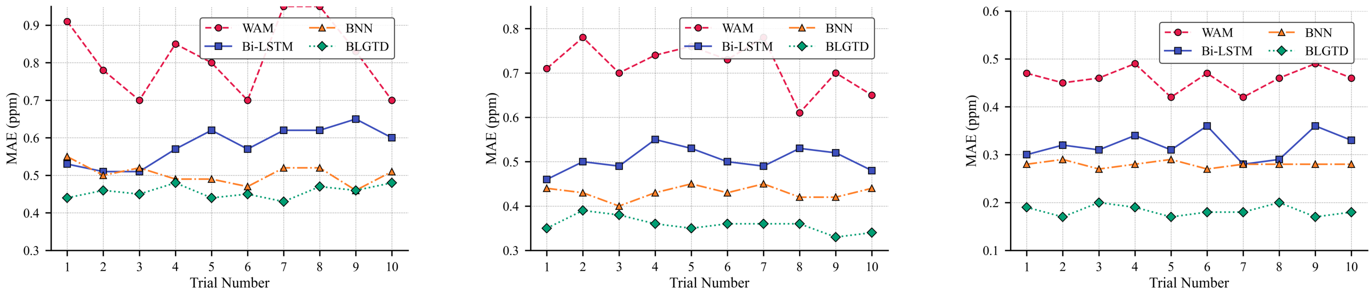
The dataset consists of methane concentration measurements collected from fixed sensors and miner-carried devices over 32 days (5 Mar–5 Apr 2024), covering $I = 128$ points, $N = 45$ sensors, $J = 57$ miners, with temperature, humidity, CH_4, CO and O_2 readings (30 s sampling).

Algorithm 1: BLGTD: Truth Discovery Based on Bi-LSTM/GRU and MC Dropout

```
Input: A = {a_{n,t}}_{n=1,t=1}^{N,T} (fixed sensor data),
  C = {c_{j,t}}_{j=1,t=1}^{J,T} (reliable miner data),
  X = {x_{i,t}}_{i=1,t=1}^{I,T} (ordinary miner data),
  P = {p_i}_{i=1}^{I} (position encoding),
  M (MC Dropout forward passes)
Output: X̂ = {X̂_{i,t}}_{i=1,t=1}^{I,T} (estimated truth),
  U = {U_{i,t}}_{i=1,t=1}^{I,T} (uncertainty estimation)
foreach i, t do
  Compute spatiotemporal feature f_{i,t} = [p_i; t];
Construct sparse input matrix Z(t) from A and C;
Process Z(t) with Bi-LSTM to obtain forward and
  backward hidden states h_t^→, h_t^←, and concatenate to
  form h_t^bi;
for i = 1 to I do
  Initialize GRU hidden state h_{i,0}^gru ← 0;
  for t = 1 to T do
    Update h_{i,t}^gru using h_t^bi and f_{i,t} via GRU;
    Compute prediction x̂_i(t) via fully connected
      layer;
Repeat forward pass M times to generate M
  prediction sequences x̂_i^(m)(t);
for t = 1 to T do
  for i = 1 to I do
    Compute prediction mean μ_i(t) and uncertainty
      U_i(t);
for t = 1 to T do
  for i = 1 to I do
    if x_i(t) ≠ NaN then
      Compute deviation δ_i(t) and weight w_i(t);
      Estimate truth
        X̂_i(t) ← w_i(t) · x_i(t) + (1 − w_i(t)) · μ_i(t);
    else
      X̂_i(t) ← μ_i(t);
return X̂, U;
```

During training, the Adam optimizer with early stopping prevents overfitting. To ensure stability and generalization, multiple experiments are conducted under varying proportions of reliable miners (TR = 0.3, 0.6, 0.9) and noise levels (SNR = 5 dB, 10 dB, 15 dB) using 5-fold cross-validation. Pilot runs showed that NLL and ECE plateau after 40 samples; we set $M = 50$ to balance calibration quality with a <3 ms latency increase. Final results are reported as averages across all runs.

We split the data into 80% for training and 20% for



(a) 30% reliable miners (TR = 0.3)
(b) 60% reliable miners (TR = 0.6)
(c) 90% reliable miners (TR = 0.9)

Fig. 3: MAE comparison of different algorithms under varying reliable miner ratios. (a) 30%, (b) 60%, (c) 90% reliable miners

testing. The experiments simulate various levels of data quality degradation and missingness to comprehensively assess the performance of BLGTD in terms of imputation accuracy, uncertainty estimation, and computational efficiency. Although the Bi-LSTM/GRU network is central to the model, hyperparameter tuning is not the main focus.

The key parameters used in the experiments are summarized in Table I.

TABLE I: Experimental Parameter Settings

Parameter	**Value / Range**
Bi-LSTM layers L	2
Units per Bi-LSTM layer	64
GRU layers	1
GRU units	32
Time series length T	20
Learning rate lr	0.0001
Batch size bs	16
Max training epochs	500
Early stopping patience	30
MC Dropout samples M	50
Positional encoding dim k	3
Fourier period τ	24
Uncertainty threshold ϵ_U	0.1 ppm^2
Safety threshold $C_{\max}$	10 ppm
Loss weighting factor λ	0.1
Reliable miner ratio (TR)	0.3 / 0.6 / 0.9
Noise level (SNR)	5 / 10 / 15 dB

B. Baseline Methods

To evaluate the effectiveness of BLGTD, we compare it with the following representative baseline algorithms:

- **Weighted Average Method (WAM)**: A conventional data fusion technique that computes a weighted average over multiple sources. It is effective for small-scale datasets with minimal temporal correlation.
- **Bidirectional LSTM (Bi-LSTM)**: A deep learning model that captures both forward and backward temporal dependencies. It is widely used in sequence modeling tasks involving long- and short-term patterns.
- **Bayesian Neural Network (BNN)** [15]: A probabilistic neural model that incorporates uncertainty estimation into predictions. BNNs are particularly suited for noisy or uncertain environments, allowing for confidence-aware decision-making.

C. Experimental Results and Analysis

1) Truth Discovery Performance: We evaluate model performance under varying levels of reliable miner ratios (TR) and signal-to-noise ratios (SNR). As shown in Table II, BLGTD consistently achieves high performance across all settings, including scenarios with severe data sparsity (TR = 0.3) and strong noise interference (SNR = 5 dB), where traditional methods degrade significantly.

BLGTD outperforms all baselines in terms of precision, recall, and F1 score. Especially under high-quality data conditions (e.g., TR = 0.9), it significantly surpasses the Weighted Average Method and Bi-LSTM. These results highlight the effectiveness of BLGTD's dynamic weighting mechanism, which enhances its adaptability to heterogeneous, noisy, and temporally dependent environments.

2) Imputation Accuracy Evaluation: Fig. 3 summarises MAE under three TR levels. At TR = 0.3, BLGTD achieves an MAE of 0.45 ± 0.03, exhibiting slight fluctuation but still significantly outperforming WAM and Bi-LSTM. This demonstrates its robustness under high data sparsity.

As TR increases to 0.6 and 0.9, the MAE rapidly drops to 0.35 ± 0.02 and 0.19 ± 0.01, respectively, indicating superior imputation accuracy. While WAM and Bi-LSTM also benefit from higher TR, their performance remains consistently inferior to BLGTD.

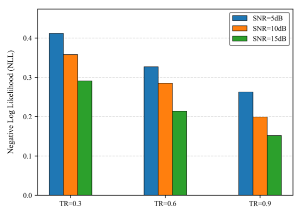
BNN performs comparably well at TR = 0.6 and 0.9, highlighting its uncertainty modeling advantage. However, it still falls short of BLGTD's consistent superiority, particularly when reliable data is abundant.

3) Uncertainty Evaluation: In coal mine environments, sparse and missing data are imputed by BLGTD via its Bi-LSTM/GRU network. To address the uncertainty inherent in such predictions, MC Dropout is employed to estimate predictive variance. During truth discovery, predictions with higher uncertainty are assigned lower weights, reducing their impact on final estimations.

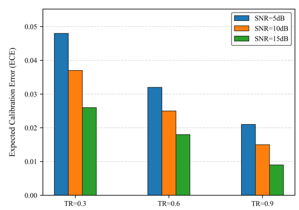
To evaluate the robustness of BLGTD under uncertainty, we analyze its performance under different SNR and TR. Two uncertainty-aware metrics are used: Negative Log-Likelihood (NLL) and Expected Calibration Error (ECE). The results are shown in Fig. 4.

TABLE II: Performance Comparison under Aligned Spatio-Temporal Cells

Condition	Value	WAM			Bi-LSTM			BNN			BLGTD		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
SNR=10 dB	TR=0.3	0.53	0.50	0.51	0.66	0.63	0.64	0.69	0.66	0.67	0.75	0.72	0.73
	TR=0.6	0.64	0.61	0.62	0.72	0.69	0.70	0.75	0.72	0.73	0.79	0.77	0.78
	TR=0.9	0.71	0.69	0.70	0.78	0.76	0.77	0.81	0.79	0.80	0.84	0.82	0.83
TR=0.6	SNR=5 dB	0.57	0.54	0.55	0.67	0.64	0.65	0.70	0.67	0.68	0.74	0.71	0.72
	SNR=10 dB	0.64	0.61	0.62	0.72	0.69	0.70	0.75	0.72	0.73	0.79	0.77	0.78
	SNR=15 dB	0.70	0.68	0.69	0.77	0.75	0.76	0.80	0.78	0.79	0.83	0.81	0.82



(a) Negative Log-Likelihood



(b) Expected Calibration Error

Fig. 4: Uncertainty evaluation under varying TR and SNR conditions. (a) NLL. (b) ECE.

As TR increases from 0.3 to 0.9, the average NLL decreases by 63.1%, and ECE drops by 81.3%, indicating better confidence calibration with more reliable data. When TR = 0.3, increasing SNR from 5 dB to 15 dB yields a 29.4% reduction in NLL; under TR = 0.9, the same SNR improvement reduces NLL by 42.2%, suggesting that reliable data can compensate for environmental noise.

In summary, BLGTD merges (i) bidirectional context, (ii) uncertainty weighting, and (iii) cross-sensor fusion; WAM lacks all, Bi-LSTM lacks (ii), and BNN lacks (iii), explaining its lead in Table II.

VI. Conclusion

This article presents BLGTD, a truth discovery method tailored for mobile crowdsensing in coal mines. By combining a Bi-LSTM/GRU hybrid network with MC Dropout, the proposed framework effectively addresses challenges such as data sparsity, temporal dependency, and electromagnetic interference. BLGTD introduces a dynamic fusion mechanism driven by predictive uncertainty. It estimates model confidence through MC Dropout and integrates it with data deviation to perform adaptive weighted fusion between observed and predicted values. The bidirectional architecture captures the spatiotemporal evolution of environmental parameters, while the uncertainty-aware strategy enhances anomaly detection and missing data imputation. Experimental results demonstrate the model's robustness and accuracy under complex sensing conditions.

Future work will explore deployment in cloud–edge–device environments (addressing energy use, latency, cost, and scale). Local preprocessing and training at the edge, combined with global model updates in the cloud, can reduce communication overhead and improve responsiveness. Moreover, integrating lightweight inference modules on miner devices could enable real-time anomaly reporting. Beyond mining, BLGTD readily generalizes to other confined industrial settings—such as chemical plants or transit tunnels—since gas dynamics and sparse sensing are similar; only local fine-tuning and threshold redefinition are needed.

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