Learning-based Smart Sensing for Energy-Sustainable WSN

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***Abstract*—Wireless sensors networks (WSNs) are gaining enormous attention for monitoring physical conditions in various application. WSNs equipped with power-hungry senors often suffer from energy sustainability. Hence, an efficient smart sensing approach is required to enhance the energy sustainability of such WSNs. A wireless node equipped with a sensor monitoring the variation of a particular parameter in time often exhibits high temporal correlation that can be studied to smartly sense the parameter. To optimize the energy consumption of these sensors and increase the network lifetime, this paper presents a learning-based adaptive sampling framework that explores the sparsity in the time series data and finds optimal sampling instants for the next measurement cycle. Principal component analysis (PCA) is used to sparsify the time domain signal and the sparse signal is reconstructed from its low-dimensional signal using the sparse Bayesian learning (SBL) method. An optimization function is formed that solves the trade-off between accuracy and energy consumption and finds the optimal sampling instants for the next measurement cycle. The performance of the proposed adaptive sampling framework is tested on air pollution monitoring dataset. The simulation results validate the energy efficiency of the proposed method. Compared to the existing adaptive sampling algorithms the proposed learning-based algorithm saves up to 58% energy with a marginally higher computational complexity while maintaining an acceptable range of sensing error.**

***Index Terms*—Adaptive sampling, energy efficiency, machine learning method, smart sensing, temporal correlation.**

I. Introduction

Wireless sensor networks (WSNs) have multiple applications across the various industries, such as health-care surveillance, environment sensing, smart city, smart agriculture, and border surveillance [1]. The sensors used in these applications consume huge energy in sensing and transmission. In many cases, sensing energy is higher than communication energy. Thus, it is required to smartly handle those power-hungry sensors by optimizing the data collection approach to increase the energy sustainability of such WSNs [2].

Owing to the nature of sparsity, the parameter being monitored by the sensor often possess temporal correlation, which can be exploited to remove redundancy in the data. Various adaptive sampling mechanisms are being used either directly in the sensor node or in the central entity (CE) that controls the operations of the field nodes either in a centralized or de-centralized manner [3]. It helps to reduce the number of samples to be measured which in turn reduces energy consumed by the sensors. The data stored in the sensor modules can be transmitted to the CE on periodic basis or non-periodically [4]. In the densely deployed WSNs, machine learning-based adaptive sensing strategies are used to select some optimal number of sensors to activate in the next cycle based on the spatio-temporal correlations among the signals. These approaches increase the energy sustainability of the network. However, the selected sensors collect data either at a fixed rate or based on some adaptive sampling methods such as Nyquist-based adaptive sampling [5]. Thus, the time-series data collected by the selected sensors often possess a high temporal correlation. To remove the redundancy in the time series data, a learning-based smart sensing technique can be applied to find the optimal sampling instants when the sensors will collect sample. In many fields such as industrial applications, data can be sent to the CE periodically. Thus, machine learning methods can be implemented for online estimation of the optimal sampling instants for the next cycle by studying the sparsity of data collected at the present cycle, which can enhance the energy sustainability of WSNs.

A. Related Work

Significant studies have been reported on data collection from a sensor node by adaptive sampling that optimizes energy consumption in both sensing and transmission compared to fixed-rate sampling. Numerous works are dedicated to node-level optimization where adaptive sampling algorithms are applied directly on the sensor node. The algorithms explore the temporal correlation on the data and vary the sampling rate with the variation of environmental phenomenon [4]–[6]. On the other hand, in network level optimization, adaptive sensing strategies are applied to find some optimal number of sensors in a densely deployed WSN [7]–[10].

Nyquist-based adaptive sampling algorithm, proposed in [5] applied in a snow monitoring sensor node. The algorithm sets the optimal sampling frequency based on Nyquist criteria by detecting the maximum frequency of the signal using Fast Fourier transform (FFT). The change in frequency of the signal is detected for some samples and a new sampling rate is assigned based on Nyquist criteria. The algorithm presented in [6] used Kalman filter (KF) to estimate the next state of the system and adjusts the sampling rate based on the estimation error. In [4], an adaptive sampling algorithm was proposed using one-way Anova model and Bartlett test, for industrial process monitoring applications. The algorithm finds the variance in the data by dividing the samples into multiple sets and compute T-statistic value using the Anova-based model.

An optimization problem was formulated in [7] for a densely deployed WSN, which selects an active set contains few sensor nodes among all the nodes available in the cluster. The optimization function minimizes the Bayesian Cramer-Rao bound (BCRB) which is the lower bound of mean squared error (MSE) of the estimated sparse signal and selects an optimal active sensor set. BCRB is computed from the spatio-temporal variations of that specific signal. Finally, sparse Bayesian learning (SBL) is used to estimate the sparse signal from the measurement vector. Two different algorithms were proposed respectively for centralized and decentralized sensor selection in [8]. The centralized sensor selection approach is a greedy method that becomes complex with the increase of the number of measurements, whereas, the decentralized approach reduces the complexity of the network by deciding its activity in the node itself without the intervention of the central node.

B. Research Gap

As noted above, several works have been found on node-level adaptation [4]–[6], where a sensor node adapts its sampling rate by studying the variations in the previously collected samples. Although these algorithms reduce the number of samples acquired to reconstructed the signal compared to the fixed sampling rate or Nyquist rate, the sensor nodes with power-hungry sensors still suffer from energy sustainability. The time series data collected by applying these algorithms still exhibits a high temporal correlation, which indicated the sparsity in the data. The signal may not be sparse in its actual domain, hence optimal adaptation of the signal in its real domain is quite challenging. However, the signal can be transformed in some other domain and sufficiently sparsify to find its principal components. Thus, by doing compressive sensing in time series data collected over a cycle, the number of samples need to acquire can be further reduced. Principle component analysis (PCA) is a popular technique to transform the signal into a sparse domain and find its significant components, which can be used to find optimal sampling instants. Several methods available in the literature to recover the original signal from its relatively low dimensional features. However, learning-based methods such as SBL, used in [7] performs superior in terms of signal estimation.

Although many works have been found on applying learning-based compressive sensing in densely deployed WSNs that optimizes the number of samples in space required to reconstruct the spatial signal, none of these works applied compressive sensing particularly in time series data to find optimal sampling positions. Thus, *learning-based adaptive sampling by exploring the temporal correlation in the data to find optimal sampling instants is yet to be studied.*

C. Contributions

The key highlights of this paper are as follows:

1) This paper presents an adaptive sampling algorithm to choose optimal sampling instants of a sensor by using PCA-based sparse signal representation and the signal is reconstructed using Sparse Bayesian learning method.
2) An optimization function is formulated that jointly optimizes the trade-off between the reconstruction error and sensing energy consumption. It explores the temporal correlations among the signal and finds an active set that contains optimal sampling instants for the next measurement cycle.
3) The proposed adaptive sampling algorithm is tested on temperature and particulate matter sensor data, collected by deploying an air pollution monitoring node in the campus.
4) The proposed framework saves up to 58% and 79% energy respectively compared to the adaptive sampling algorithms given in [4] and [5] with relatively higher computational complexity, while maintaining a sensing error on the same order as in [4].

Organization: Section II contains the preliminaries that includes the data acquisition model, sparse signal representation and SBL based signal recovery model, followed by the proposed adaptive sampling framework presented in Section III. Section IV outlines the experimental setup used for data collection and results, followed by concluding remarks in V.

Notations: $\mathcal{Z}$ and $\underline{\mathbf{Z}} \in \mathbb{R}^{M\times N}$ respectively denotes a set and a real valued matrix of size $M \times N$, $\mathbf{z} \in \mathbb{R}^{N\times 1}$ represents a vector having N elements. Cardinality of set $\mathcal{M}$ is represented as $|\mathcal{M}| = M$.

II. Preliminaries

This section contains the data acquisition model for the proposed framework followed by the sparse representation of the signal using PCA and application of sparse Bayesian learning method for signal recovery.

A. Data Acquisition Model

Consider a wireless sensor node equipped with multiple sensors to capture the variation of multiple parameters in the environment. Let a sensor collects data at a fixed sampling interval and transmits periodically at the central entity (CE) which is placed at a fixed point nearby. Let the period between two data transmission, called measurement cycle is divided into N equal number of intervals. The sensor collects a sample at the end of each interval. Thus, there are N sampling instants at every measurement cycle of length $\mathcal{T} = Nt$, where t is the sampling interval. Since the time series data exhibits a strong temporal correlation, the signal can be reconstructed with $M << N$ number of samples, where M is the number of optimal sampling instants. The value of M and the optimal sampling points changes with the dynamics of the system. A fixed length of measurement cycle is required to maintain a fixed feature dimension (N), for the simplicity of the operation. If $\mathcal{T}$ is same for all the sensors in the node, the values of N and M are larger for the fast-varying signals compared to the slowly-varying signals.

Let $\mathcal{M}^x$ be the set contains the optimal sampling instants of a particular sensor at the x^{th} measurement cycle, called active set and $|\mathcal{M}^x| = M^x$. For N samples total 2^N number of active sets can be constructed. $\mathcal{M}^x \subseteq \mathcal{P}$, where $\mathcal{P} =$

$\{1, 2, \cdots, N\}$ contains all the sampling instants. Each active set $\mathcal{M}^x$ corresponds to a binary sensing matrix $\underline{\mathbf{M}}^x \in \mathbb{R}^{M^x \times N}$ and a diagonal matrix $\underline{\tilde{\mathbf{M}}}^x = \underline{\mathbf{M}}^{xT}\underline{\mathbf{M}}^x \in \mathbb{R}^{N\times N}$. Each row of $\underline{\mathbf{M}}^x$ represents one sampling instant. If n is the m^{th} element of $\mathcal{M}^x$, $\underline{\mathbf{M}}^x(m,n) = 1; \forall n, m \in \mathcal{M}^x$. Thus, $\underline{\tilde{\mathbf{M}}}^x(n,n) = 1; \forall n \in \mathcal{M}^x$.

If $\mathbf{z}^x = \{Z_1^x, Z_2^x, \cdots, Z_N^x\}^T \in \mathbb{R}^{N\times 1}$ is the vector contains the true values of the N samples and $\mathcal{M}^x$ is the optimal active set, the measurement vector at the x^{th} measurement cycle is given by[11],

$$\tilde{\mathbf{y}}^x = \underline{\mathbf{M}}^x \mathbf{z}^x + \mathbf{n}^x, \tag{1}$$

where $\mathbf{n}^x \in \mathbb{R}^{M^x \times 1}$ is the additive white Gaussian noise vector. Each component of $\mathbf{n}^x$ is identically and independently distributed having mean zero and variance σ^2.

B. Sparse Signal Representation and Signal Recovery

Let, initially K number of samples are collected by the sensor with fixed sampling interval t. The samples are divided into $I = round(K/N)$ number of sets. Thus, the initial training matrix is formed as $\underline{\mathbf{Z}} \in \mathbb{R}^{I\times N}$. If $\bar{\mathbf{z}} \in \mathbb{R}^{N\times 1}$ and $\hat{\underline{\Sigma}} \in \mathbb{R}^{N\times N}$ are respectively the mean vector and covariance matrix of $\underline{\mathbf{Z}}$, then each component of $\bar{\mathbf{z}}$ and $\hat{\underline{\Sigma}}$ are calculated as,

$$\bar{Z}_n = \frac{1}{I}\sum_{i=1}^{I} Z_n^i; \forall n \in \mathcal{P}, \tag{2}$$

$$\hat{\underline{\Sigma}}(m,n) = \frac{1}{I}\sum_{i=1}^{I}(Z_m^i - \bar{Z}_n)(Z_m^i - \bar{Z}_n)^T; \forall m, n \in \mathcal{P}. \tag{3}$$

The covariance matrix can be represented by its eigen values and eigen vector as $\hat{\underline{\Sigma}}(m,n) = \underline{\mathbf{A}}^{xT}\underline{\Gamma}^x\underline{\mathbf{A}}^x$, where $\underline{\mathbf{A}}^x$ is a sparsifying matrix that transforms the true signal vector $\mathbf{z}^x$ to a sparse vector $\mathbf{s}^x$. Thus the sparse representation of $\mathbf{z}^x$ using PCA is given by,

$$\mathbf{z}^x = \bar{\mathbf{z}} + \underline{\mathbf{A}}^x \mathbf{s}^x. \tag{4}$$

$\underline{\Gamma}^x$ is a diagonal matrix whose diagonals elements are the eigen values of $\hat{\underline{\Sigma}}$. The equivalent measurement vector corresponds to the sparse signal vector $\mathbf{s}^x$ is given by [7],

$$\mathbf{y}^x = \underline{\Theta}^x \mathbf{s}^x + \mathbf{n}^x, \tag{5}$$

where $\underline{\Theta}^x = \underline{\mathbf{M}}^x\underline{\mathbf{A}}^x$ is the dictionary matrix. Let, $\underline{\mathbf{S}} \in \mathbb{R}^{I\times N}$ is the equivalent sparse matrix of the training matrix $\underline{\mathbf{Z}}$. $\mathbf{y}^x$ can be calculated from $\tilde{\mathbf{y}}^x$ as,

$$\mathbf{y}^x = \tilde{\mathbf{y}}^x - \underline{\mathbf{M}}^x \bar{\mathbf{z}} \tag{6}$$

Given $\tilde{\mathbf{y}}^x$ and $\underline{\mathbf{A}}^x$, the sparse signal vector $\mathbf{s}^x$ can be estimated using sparse Bayesian learning method described in [7]. Since $\mathbf{z}^x$ is unknown, $\underline{\mathbf{A}}^x$ can not be estimated. Due to the slowly-varying nature of the temporal signal $\underline{\mathbf{A}}^x \approx \underline{\mathbf{A}}^{x-1}$ can be estimated to find $\mathbf{s}^x$ at the x^{th} measurement cycle. $\underline{\mathbf{A}}^{x-1}$ is estimated from the covariance matrix $\hat{\underline{\Sigma}}^{x-1}$ which is calculated from $\underline{\mathbf{Z}}^{x-1} \in \mathbb{R}^{I\times N}$ which is formed by the immediate previous K samples. Similarly the updated mean vector $\bar{\mathbf{z}}^{x-1}$ for $\underline{\mathbf{Z}}^{x-1}$ is also calculated using (2).

SBL can estimate the high-dimensional sparse signal from its low-dimensional signal vector by using iterative expectation maximization (EM) algorithm. At each measurement cycle, SBL assigns a Gaussian prior on $\mathbf{s}^x$, parameterized by the variance of each component of $\mathbf{s}^x$, which fits well on sensing signals. Considering $\mathbf{s}^x$ as a latent variable, EM estimates the hyperparameter vector γ^x, where $\gamma^x(n)$ is the variance of the n^{th} column vector of $\underline{\mathbf{S}}^x$. Thus, the posterior distribution of $\mathbf{s}^x$ in the i^{th} iteration is $p(\mathbf{s}^x|\mathbf{y}^x;\gamma^{x(i)}) \sim N(\mu_{\mathbf{s}^x}^{(i)}, \underline{\Sigma}_{\mathbf{s}^x}^{(i)})$, where $\mu_{\mathbf{s}^x}^{(i)} \in \mathbb{R}^{N\times 1}$ and $\underline{\Sigma}_{\mathbf{s}^x}^{(i)} \in \mathbb{R}^{N\times N}$ are respectively the posteriori mean vector and the covariance matrix. In the i^{th} iteration $\mu_{\mathbf{s}^x}^{(i)}$ and $\underline{\Sigma}_{\mathbf{s}^x}^{(i)}$ can be calculated using (7) and (8), respectively [7].

$$\mu_{\mathbf{s}^x}^{(i)} = \sigma^{-2}\underline{\Sigma}_{\mathbf{s}^x}^{(i)}\underline{\Theta}^{xT}\mathbf{y}^x, \tag{7}$$

$$\underline{\Sigma}_{\mathbf{s}^x}^{(i)} = (\hat{\underline{\Gamma}^x}^{(i)} - \hat{\underline{\Gamma}^x}^{(i)}\underline{\Theta}^{xT}(\sigma^2\mathbf{I}_{M^x} + \underline{\Theta}^x\hat{\underline{\Gamma}^x}^{(i)}\underline{\Theta}^{xT})^{-1}\underline{\Theta}^x\hat{\underline{\Gamma}^x}^{(i)}), \tag{8}$$

$$\hat{\gamma^x}^{(i+1)}(n) = \underline{\Sigma}_{\mathbf{s}^x}^{(i)}(n,n) + \mu_{\mathbf{s}^x}^{(i)}(n,n)^2. \tag{9}$$

$\hat{\underline{\Gamma}^x}^{(i)}$ is the diagonal matrix having $\hat{\gamma^x}^{(i)}(n)$ as the n^{th} diagonal element. $\hat{\underline{\Gamma}^x}^{(i+1)}$ for the $(i+1)^{th}$ iteration is calculated from (9). After L number of iterations the final mean vector $\mu_{\mathbf{s}^x}^{(L)}$ is estimated as sparse vector $\mathbf{s}^x$ which is further used to find $\mathbf{z}^x$ using (4) [7].

III. Adaptive Sampling Framework

This section outlines the formulation of optimization function to find an active set contains optimal sampling instants for the next cycle followed by the proposed adaptive sampling algorithm.

An active set $\mathcal{M}^x$ at the x^{th} measurement cycle has to be chosen such that it minimizes both the signal reconstruction error and sensing energy consumption. Assuming the sensing energy consumption of a sensor is time-independent, the total energy consumed by the sensor increases linearly with the increase of $\mathcal{M}^x$. Whereas, the reconstruction error reduces with the increase of $\mathcal{M}^x$. Thus an active set has to be chosen that solves the trade-off between the two performance parameters of the system.

Let $\hat{\mathbf{s}}^x$ be the sparse signal vector recovered using SBL, discussed in Section II-B. The mean-squared error is calculated as, MSE=$\mathbb{E}\{||\mathbf{s}^x - \hat{\mathbf{s}}^x||\}$. MSE is considered as the performance metric that determines the signal estimation accuracy. By minimizing the estimation error on $\mathbf{s}^x$, reconstruction error on $\mathbf{z}^x$ can be minimized.

Bayesian Cramer-Rao bound (BCRB) provides a lower bound on the MSE to estimate sparse vector $\mathbf{s}^x$. Since, $\mathbb{E}\{||\mathbf{s}^x - \hat{\mathbf{s}}^x||\} \geq$ BCRB, by minimizing BCRB the MSE of $\mathbf{s}^x$ can be minimized. As discussed in [7] BCRB is calculated as,

$$BCRB = Tr\{(\sigma^{-2}\underline{\mathbf{A}}^{xT}\underline{\tilde{\mathbf{M}}}^x\underline{\mathbf{A}}^x + (\underline{\Gamma}^x)^{-1})^{-1}\} \tag{10}$$

Thus a joint optimization function to solve the trade-off between error and energy consumption to find optimal active set $\mathcal{M}^x$ for the x^{th} measurement cycle is formed as,

$$\begin{aligned} &\underset{\underline{\tilde{\mathbf{M}}}^x \forall \mathcal{M}^x \subseteq \mathcal{P}}{\text{minimize}} \; Tr\{(\sigma^{-2}\underline{\mathbf{A}}^{xT}\underline{\tilde{\mathbf{M}}}^x\underline{\mathbf{A}}^x + (\underline{\Gamma}^x)^{-1})^{-1}\}(\sum_{i=1}^{N}\underline{\tilde{\mathbf{M}}}^x(n,n))E_n \\ &\text{s. t. } BCRB \in [\alpha, \beta] \text{ and} \\ &\underline{\tilde{\mathbf{M}}}^x(n,n) \in [0,1]. \end{aligned} \tag{11}$$

E_n is the energy consumed by the sensor to collect one sample. In the above formulation, equal weight is given to

Algorithm 1: Adaptive sampling algorithm

Input: Sampled data received from the sensor node Initialize: $e = 1$, N, K, t, $\underline{\mathbf{Z}}$
if *e=1* **then**
  Calculate $\bar{\mathbf{z}}$ and $\hat{\underline{\Sigma}}$ using (2) and (3) for $\underline{\mathbf{Z}}$.
  Find $\underline{\mathbf{A}}^0$ and $\underline{\Gamma}^0$ for $\hat{\underline{\Sigma}}$.
  Find $\hat{\underline{\Gamma}}^0$ for $\underline{\mathbf{S}}^1$
  Set $\underline{\mathbf{A}}^1 = \underline{\mathbf{A}}^0$, $\hat{\underline{\Gamma}}^1 = \hat{\underline{\Gamma}}^0$
  Obtain $\mathcal{M}^1$ by solving (11).
  Set $\mathcal{T} = Nt, e = 0, x = 0$
else
  Calculate $\mathbf{y}^x$ using (6)
  Estimate $\hat{\mathbf{s}}^x$ from $\underline{\mathbf{A}}^x$, $\hat{\underline{\Gamma}}^x$ and $\mathcal{M}^x$ using (7), (8) and (9).
  Calculate $\hat{\mathbf{z}}^x$ from $\hat{\mathbf{s}}^x$ and $\underline{\mathbf{A}}^x$ using (4).
  Update $\underline{\mathbf{Z}}^x$ and find $\bar{\mathbf{z}}^x$, $\hat{\underline{\Sigma}}^x$ for the updated $\underline{\mathbf{Z}}^x$
  Find $\underline{\mathbf{A}}^x$ and $\underline{\Gamma}^x$ for $\hat{\underline{\Sigma}}^x$.
  Update $\underline{\mathbf{S}}^x$ and find $\hat{\underline{\Gamma}}^x$ for the updated $\underline{\mathbf{S}}^x$
  Set $\underline{\mathbf{A}}^{x+1} = \underline{\mathbf{A}}^x$, $\hat{\underline{\Gamma}}^{x+1} = \hat{\underline{\Gamma}}^x$
  Obtain $\mathcal{M}^{x+1}$ by solving (11).
  Set $\mathcal{T} = Nt, e = 0$
  while $\mathcal{M}^{x+1} \geq \mathcal{M}_{th}$ **do**
    Set $\mathcal{T} = Kt, e = 1$
  end
end
Set $x = x + 1$
Output: Transmit $\mathcal{T}, \mathcal{M}^x, e$ to the node

both the performance parameters, however $\underline{\tilde{\mathbf{M}}}^x$ is chosen such that the BCRB remains within a bound $[\alpha, \beta]$ given in the constraints. The values of α and β have to be chosen such that the MSE remains within an acceptable range. According to the analysis given in [7], BCRB is convex, hence the optimization function, given in (11) always returns an active set that contains the optimal sampling instants. The active set $\mathcal{M}^x$ of the corresponding diagonal matrix $\underline{\tilde{\mathbf{M}}}^x$ contains the optimal sampling instants of that measurement cycle.

The proposed algorithm, given in *Algorithm*1 is programmed at the CE that works based on a feedback mechanism. The CE receives data from the node periodically, executes the algorithm, and transmits information containing the active set and status flag e. Since MSE increases with time, more number of samples need to be taken to maintain the BCRB within the limit. This is solved by retraining the model upon detecting M^x higher than a user-defined threshold M_{th}.

Let, Δ be the total communication energy required for one transmission. $\Delta = \Delta_1 + \Delta_2$, where Δ_1 and Δ_2 are the wake up and data transmission energy, respectively. Δ_1 is assumed to be fixed and Δ_2 increases with the increase in the number of samples to be transmitted. Since Δ_1 is the initial energy required to turn on the communication module, it is much higher than Δ_2. Thus, total communication energy up to some measurement cycle reduces with the increase in $\mathcal{T}$. On the other hand, if $\mathcal{T}$ increases the signal estimation error increases due to the large variation in environmental conditions between two cycles. To maintain good accuracy more number of samples need to be collected, which in turn increases the sensing energy consumption. Thus $\mathcal{T}$ has to be chosen by considering the trade-off between the two energy consumptions of the system. The fixed sampling interval (t) can be obtained from the the power spectral density of the signal as discussed in Section IV-B. While retraining the model, these parameters are also updated based on the current samples.

A. Complexity of the Proposed Framework

The computational complexity of SBL model with L number of iterations is $\mathcal{O}(LM^{x^3})$, where M^x is the number of optimal sapling instants at the x^{th} measurement cycle. While complexity in finding optimal sampling instants using the optimization function is $\mathcal{O}(2^N N^3)$. On the other hand, the complexity of the adaptive sampling algorithm given in [4] is $\mathcal{O}(M^x)$.

IV. Experimental Setup and Results

A brief overview of the experimental setup used for data collection and the simulation results of the algorithm is discussed in this section.

A. Experimental Setup for Data Collection

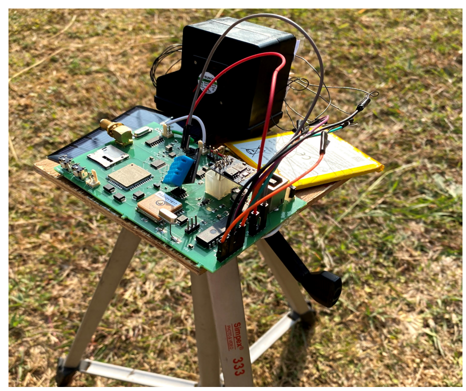
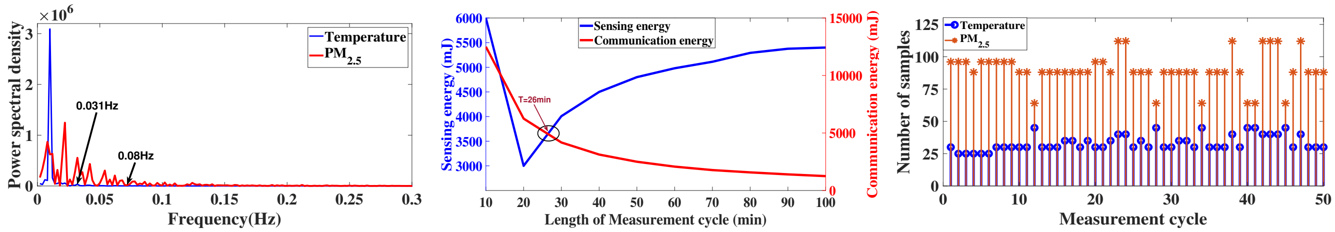


Fig. 1: Prototype of air pollution monitoring sensor board.

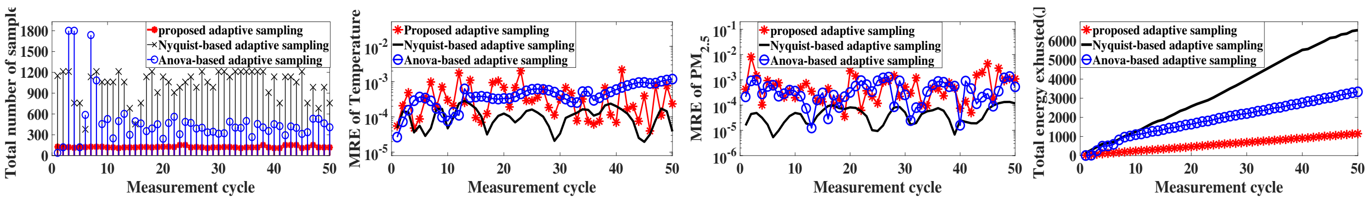
To validate the efficiency and efficacy of the proposed learning-based adaptive sampling algorithm explained in Section III on real-life applications, an air pollution monitoring sensor node is deployed in the campus. The node is equipped with a DHT11 sensor to measure the temperature and humidity, and an alphasence OPC-N3 sensor to measure the concentration of the particulate matters having diameter less than 2.5μm ($PM_{2.5}$). The energy consumed by the DHT11 and OPC-N3 to collect one good sample are 0.012 J and 0.25 J, respectively [12]. In the current study, the time-series data of only the temperature and $PM_{2.5}$ signals are considered.

The temporal correlations of the temperature and $PM_{2.5}$ sensor data are explored independently and it is observed that the signals exhibit high temporal correlations between two consecutive samples. The temporal correlation coefficients for temperature and $PM_{2.5}$ are respectively in the range of $0.88 - 0.95$ and $0.81 - 0.9$, which indicates the sparsity nature of data [13]. A set of raw data is collected at a fixed sampling rate higher than the Nyquist rate from the experimental setup and the algorithm described in Section III is applied on that dataset for both the parameters individually. The simulation results are explained in IV-B.



(a) (b) (c)

Fig. 2: (a) Power spectral density of the sensing signals, (b) measurement cycle versus sensing and communication energy, and (c) Number of samples collected for temperature and $PM_{2.5}$ parameters at various measurement cycles.



(a) (b) (c) (d)

Fig. 3: Comparison of (a) number of samples, (b) reconstruction error of temperature, (c) reconstruction error of $PM_{2.5}$, and (d) Total energy comsumed by the node at different measurement cycles in the proposed framework, Anova-based adaptive sampling [4], and Nyquist-based adaptive sampling [5].

TABLE I: Performance comparison

Parameters	Proposed framework	Anova-based model	Nyquist-based model
Average energy consumption (J)	26.92	66.67	131.18
Average error of temperature (MRE)	4.73×10^{-4}	4.13×10^{-4}	9.35×10^{-5}
Average error of $PM_{2.5}$ (MRE)	8.51×10^{-4}	6.74×10^{-4}	4.96×10^{-5}

B. Results and Discussions

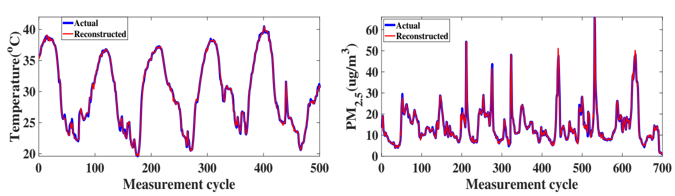


Fig. 4: Reconstruction performance of the proposed algorithm.

The adaptive sampling algorithm proposed in III *Algorithm*1 is applied on the time series data of temperature and $PM_{2.5}$ signals collected by the experimental setup given in Section IV-A. The simulation results of the algorithm are presented in Fig. 3 and Fig. 2.

The power spectral densities (PSDs) of the temperature and $PM_{2.5}$ signals are studied to find optimal fixed sampling intervals for both the parameters to divide the length of measurement cycle $\mathcal{T}$. In Fig. 2(a) it can be observed that 99% power of the temperature and $PM_{2.5}$ signals lies within $0 - 0.025$ Hz and $0 - 0.08$ Hz frequency range, respectively. Hence a fixed sampling interval of $t = 30$ sec and $t = 12$ sec are considered, respectively for simulation. The wake up and transmission energy are set as $\Delta_1 = 24$ mJ and $\Delta_2 = 0.23$ mJ, respectively [14]. Fig. 2(b) shows the trade-off between sensing and communication energy with the change in $\mathcal{T}$. The total sensing energy increases with $\mathcal{T}$ while communication energy decreases with $\mathcal{T}$. Hence, the crossover point $\mathcal{T} = 26$ min is set as the length of measurement cycle for both the parameters which is updated at every retraining point. Thus, the total number of sampling instants are chosen as $N = 52$ for temperature and $N = 130$ for $PM_{2.5}$. The noise variance for both the parameters are set as $\sigma^2 = 10^{-6}$, as given in [15]. Different value of $\mathcal{T}$ can be chosen for different parameters, which increases the communication energy, as the communication module has to be turned ON at different point of time. Thus, the length of measurement cycle is chosen to be equal for both the parameters to optimize the energy consumption.

The optimization function finds different active sets at different measurement cycles based on the dynamics of the system. Fig. 2(c) depicts that the optimal number of samples are different for different parameters. Since, the temperature signal is slowly-varying it can be reconstructed from less number of samples. Where as, due to the fast-varying nature of $PM_{2.5}$ signal, it requires more number of samples to reconstruct. Thus, *the proposed algorithm is adaptive to the dynamics of sensing signals.* The optimal samples vary in terms of position as well as the number, which can be obtained by solving the proposed optimization function.

Fig. 3(a) presents a comparison between the total number of samples collected by the node at various measurement cycle. The total number of samples collected in the proposed method at a particular measurement cycle is much lower than the other two cases. However, the signals are reconstructed efficiently from these few samples as shown in Fig. 4.

To analyze the performance of the proposed algorithm, the mean relative error (MRE) of the reconstructed signals at the CE is considered. The MREs are compared with the MRE achieved by the other adaptive sampling algorithms given in [4] and [5]. Since the proposed framework is dedicated to the analysis of a time series signal, the above two works are found to be most appropriate for comparison. According to [5], MRE below 10^{-2} is acceptable. However, the MRE achieved by the algorithm given in [4] is taken as a benchmark to compare the performances. By exploring different values of α and β, it is decided that BCRB $\in [9.5 \times 10^{-5}, 3.1 \times 10^{-4}]$ gives MRE below 10^{-3} for both the parameters, which is similar to the error performance of Anova-based model.

The MRE in the x^{th} measurement cycle is given by,

$$MRE^x = \frac{1}{N}\sum_{i=1}^{N} \frac{|z_i^x - \widehat{z}_i^x|}{|z_i^x|}, \tag{12}$$

where z_i^x and $\widehat{z}_i^x$ are respectively the i^{th} samples of the actual and reconstructed data sequence in x^{th} measurement cycle.

Fig. 3(b) shows that the MRE achieved in case of temperature signal with proposed algorithm slightly higher than Nyquist-based model [5] but similar to the Anova-based model [4]. Similarly the MRE for $\mathrm{PM}_{2.5}$, shown in Fig. 3(c) is comparable with the Anova-based model.

A comparison of total energy consumption at the node using the proposed method with the Nyquist-based model and Anova-based model is shown in Fig. 3(d). It can be clearly observed that the total energy exhausted from the battery at the end of every measurement cycle is much lower in the proposed case compared to the other two cases. The energy efficiency is calculated using (13).

$$\text{Energy saved} = \left[\frac{1}{X}\sum_{x=1}^{X} \frac{E_a^x - E_p^x}{E_a^x}\right] \times 100\%. \tag{13}$$

In (13), E_p^x and E_a^x are respectively the total energy consumed by the sensor up to x measurement cycles using the proposed model and the existing models. The proposed adaptive sampling algorithm saves up to 58% and 79% energy compared to the Anova-based [4] and Nyquist-based [5] adaptive sampling algorithms, respectively.

The performance comparison in terms of error and energy consumption is listed in Table-I. It can be observed that the average of the total energy consumed by the two sensors in sensing up to a large number measurement cycles is minimum in the proposed framework with 14.5% and 26% increase in MRE for temperature and $\mathrm{PM}_{2.5}$, respectively compared to the Anova-based model [4]. However, the average errors are less than 10^{-2} which indicates a good estimation of signals [5].

Remark 1: *The simulation results demonstrate that the proposed learning-based adaptive sampling algorithm is highly energy-efficient while choosing optimal sampling instants within an error bound based on the process dynamics.*

V. Concluding Remarks

The temporal correlation of a dynamic sensing signal has been studied in this work. Considering pollution monitoring as a use case, it has been demonstrated that the proposed learning-based adaptive sampling framework outperforms the existing competitive methods in terms of significantly higher energy efficiency without compromising on the sensing quality. The proposed framework intelligently exploits the redundant information content in a slowly-varying signal. In particular, the present states caries a lot of information about the next states. Thus, by exploring the sparsity in the data collected at the present cycle, optimal sampling instants for the next cycle can be decided. Extensive simulation results have validated the efficacy of the proposed algorithm. We intend to pursue incorporation of the proposed smart sensing along with ambient energy driven operation, leading to green and energy sustainable WSN as a future direction of research.

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