IMPLEMENTATION OF ADAPTIVE SENSOR SELECTION FRAMEWORK

Supervisors:

Prof. Swades De

Department of Electrical Engineering

IIT Delhi

Submitted by

Shakthi priya M

Summer Research Fellow

GCT, Coimbatore

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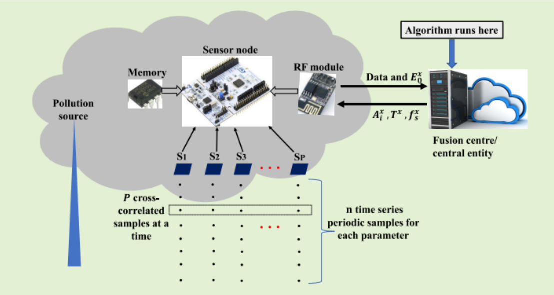


Figure: Process overflow of Framework [1]

Adaptive Sensor Selection Framework

Software requirements

To implement an intelligence-based Adaptive Sensor Selection Framework to select the optimal sensor sets for every measurement cycle, the following software are required.

- Python 3.9
- VS Code
- Anaconda
- Sci-kit library

System model

- The sensor hub consists of multiple sensors to monitor multiple sensing parameters in the environment. The measurement vector for each parameter in the x^{th} measurement cycle is denoted as,

$$z^x = y^x + \eta^x \tag{1}$$

  where z^x, y^x are respectively the measured data and true data vector and η^x is the measurement noise vector.

- The sensors deployed in the environment, sense the spatio-temporally varying environmental parameters. The sensing parameters exhibit cross-correlation among them which can be used to predict one parameter from the other.

- Based on the possible combinations of sensors, an optimal active sensor set is selected for the next measurement cycle based on the correlation of the parameters, consumption of energy by the sensors of the active set, and the availability of energy at the node

The mean cross-correlation between the parameters of A_i^x and B_i^x is

$$C_i^x = \frac{1}{B_i^x}\Sigma_{k=1}^{B_i^x}\frac{1}{c_{i,k}^x}\Sigma_{q=1}^{c_{i,k}^x}|c^x(q,k)|; \forall k \in B_i^x \quad and \quad q \in \hat{C}_{i,k}^x \tag{2}$$

$\hat{C}_{i,k}^x$ be the set which contain the parameters of A_i^x highly correlated with k^{th} parameters of B_i^x.

The reward function is formulated as

$$R_i^x = \frac{\lambda^x \left(C_i^x\right)^\gamma}{v^x \left(E_i^x\right)^\beta} \tag{3}$$

where $\lambda^x \cong \frac{E_0^x}{E_{batt}}$ is the regularized energy available at the node and $v^x = \max_{i \in S^x} \frac{(C_i^x)^\gamma}{(E_i^x)^\beta}$

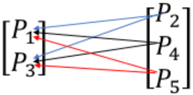
The objective function for selecting an optimal sensor set at the $(x+1)^{th}$ measurement cycle is:

$$A_i^{x+1} = \max_{i \in S_x} \frac{1}{x}\Sigma_{t=1}^{x}\frac{\lambda^t \left(C_i^t\right)^\gamma}{v^t \left(E_i^t\right)^\beta} + \sqrt{\frac{2\ln\frac{1}{\partial}}{T_i^x}} \tag{4}$$

with constraint $C_i^x > c_{th}$ and $I^{(x+1)}E_i^{(x+1)} < E_0^x$

Discounted UCB algorithm II

$P = \{P_1, P_2, P_3, P_4, P_5\}$
$A_1 = \{P_1, P_3\}$
$B_1 = \{P_2, P_4, P_5\}$



If $c(P_1, P_2) > c_{th}$ then they are correlated

$c_{P_2} = \sum_{x \in A_1} I_{c(x, P_2) > c_{th}}$	$C_{P_2} = \{P_1\}$	$c(P_1, P_2) > c_{th}$	$c(P_2, P_3) < c_{th}$
$c_{P_4} = \sum_{x \in A_1} I_{c(x, P_4) > c_{th}}$	$C_{P_4} = \{P_1, P_3\}$	$c(P_1, P_4) > c_{th}$	$c(P_3, P_4) > c_{th}$
$c_{P_5} = \sum_{x \in A_1} I_{c(x, P_5) > c_{th}}$	$C_{P_5} = \{P_3\}$	$c(P_1, P_5) < c_{th}$	$c(P_3, P_5) > c_{th}$

$$C_1 = \frac{1}{3}\left(c(P_1, P_2) + \frac{1}{2}\big(c(P_1, P_4) + c(P_3, P_4)\big) + c(P_3, P_5) \right) \qquad if \quad c_p > 0 \quad \forall\, p \in B_1$$
$$C_1 = 0 \quad ; \qquad otherwise$$

GPR based predictive model

$$Prior : Pr(f(z*)) = \int Pr\left(f|w,(z*)\right) Pr\left(w\right) dw \tag{5}$$

$Pr\left(w\right)$ is assumed Gaussian and $Pr\left(f|w,(z*)\right)$ is deterministic. Hence $Pr(f(z*))$ is Gaussian.

$$Posterior : Pr(f(z*)|Z,y) = \int Pr\left(f|w,(z*)\right) Pr\left(w|\ Z,\ y\right) dw \tag{6}$$

where $Prf(z*)|Z,y)$ is also Gaussian in nature.

The kernel function used in the GPR modeling is

$$k(\mathbf{z}_{\mathcal{A}_i,r},\mathbf{z}_{\mathcal{A}_i,s}) = e^{-\frac{1}{2l^2}\sum\limits_{m=1}^{A_i}|z_{\mathcal{A}_i,r}(m)-z_{\mathcal{A}_i,s}(m)|^2} + \sigma^2\delta_{rs}. \tag{7}$$

Algorithm 1: Active sensor set selection at the central entity

Input: Sampled data and E_0^x from the sensor node
if *e=1* **then**
    Retrain and test the model with recently collected samples
    Find $PE_i; \forall i \in \mathcal{S}$
    Set $x = 0$, $e = 0$, and $\mathcal{T} = \mathcal{T}'$
else
    if *e'=1* **then**
        Find $PE_i^x; \forall i \in \mathcal{S}$
        if $|PE_i^x - PE_i| \leq \epsilon_i; \forall i \in \mathcal{S}^x$ **then**
            Calculate $y(d)$; $\mathcal{T} = \frac{1}{y(d)}$; $e' = 0$
        else
            Set $e' = 0$, and $e = 1$
            Find maximum frequency $f_m^p; \forall p \in \mathcal{P}$ using FFT
            Set $f_s = 2 \times max\{f_m^1, f_m^2, f_m^3 \ldots . f_m^P\}$; $\mathcal{T} = \frac{n}{f_s}$
        end
    else
        Predict the missing samples using the appropriate sub-model of GPR
        Calculate $y(d)$; $\mathcal{T} = \frac{1}{y(d)}$
        Find $ct_p^x; \forall p \in \mathcal{P}$
        while $ct_p^x \ngeq ct_{p,th}; \forall p \in \mathcal{P}$ **do**
            Set $e' = 1$
        end
    end
end
while *e=0* **do**
    Construct $\mathcal{S}^x$ and calculate C_i^x and $E_i^x; \forall i \in \mathcal{S}^x$ respectively
    Find optimal active sensor set $\mathcal{A}_i^{x+1}$
    Find maximum frequency $f_m^p; \forall p \in \mathcal{P}$ using FFT
    Set $f_s = 2 \times max\{f_m^1, f_m^2, f_m^3 \ldots . f_m^p\}$
end
Set $x = x + 1$
Output: Transmit updated $\mathcal{T}$, f_s, $\mathcal{A}_i^{x+1}$, e, e' to the node

Implementation of Adaptive Framework

Experimental setup I

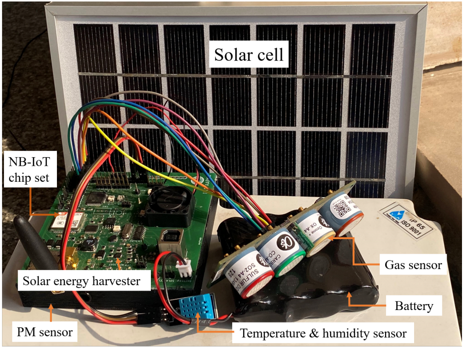
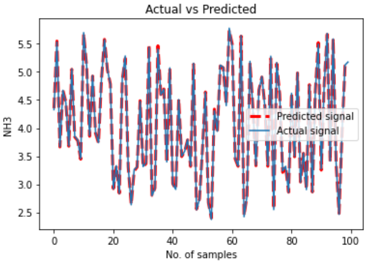
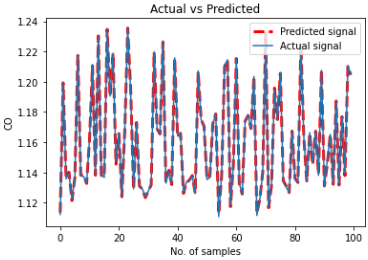


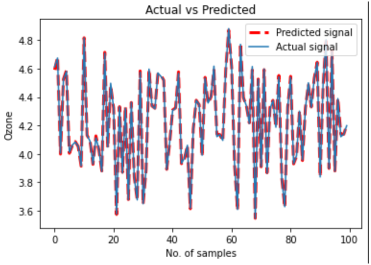
Figure: Hardware components of APMD

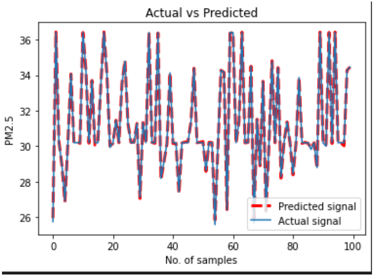
Experimental setup II

Figure: Hardware setup with solar panel


Actual vs Predicted
NH3
5.5
5.0
4.5
4.0
3.5
3.0
2.5
0
20
40
60
80
100
No. of samples
Predicted signal
Actual signal


Actual vs Predicted
CO
1.24
1.22
1.20
1.18
1.16
1.14
1.12
0
20
40
60
80
100
No. of samples
Predicted signal
Actual signal


Actual vs Predicted
Ozone
4.8
4.6
4.4
4.2
4.0
3.8
3.6
0
20
40
60
80
100
No. of samples
Predicted signal
Actual signal


Actual vs Predicted
PM2.5
36
34
32
30
28
26
0
20
40
60
80
100
No. of samples
Predicted signal
Actual signal

Outputs II

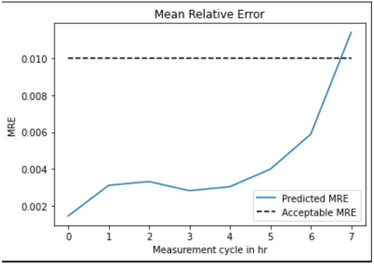
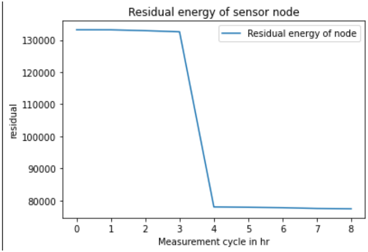


Figure: Mean relative error



[1] S. Ghosh, S. De, S. Chatterjee, and M. Portmann, "Learning-based adaptive sensor selection framework for multi-sensing wsn," *IEEE Sensors Journal*, vol. 21, no. 12, pp. 13 551–13 563, 2021. DOI: 10.1109/JSEN.2021.3069264.

THANK YOU