SUMMER RESEARCH FELLOWSHIP PROGRAM - 2022

Final Report

Implementation of Adaptive Sensor Selection Framework

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Abstract

Internet of Things (IoT) based sensor nodes are mostly battery operated and it is limited to the storage capacity and often suffers from the sustainability of energy. To increase the lifetime of these sensor hubs, various adaptive sensor selection frameworks are presented in the literature to optimally adapt the sensors to reduce energy consumption with good sensing quality. Multiple sensors monitoring the environmental parameters often exhibit a correlation between them which makes the system to be predictive. Multi-parameter sensor node hub consists of numerous sensors for monitoring multiple parameters in the habitat. A novel selection of sensor framework is presented where a learning-based enhancement strategy is developed[2] and presented using Upper Confidence Bound (UCB) to select an optimal sensor online for a period of measurement cycle based on the cross-correlation of various monitoring parameters in the environment. Through the exploitation of the correlation, prediction can be made for the sleep sensors based on the Gaussian Process Regression. Gaussian Process Regressor (GPR) gives 95% confidence level in prediction accuracy. The energy of the bandwidth is saved by taking the temporal correlation of the parameters and the sampling rate of each parameter is made adaptive. Through this, energy consumption by the sensor and the bandwidth is reduced by maintaining acceptable sensing error. WSN zone data is sent to the central entity which can be analysed to build a mechanism of feedback to adapt the parameters of the system.

Keywords: Multi-parameter sensor hub, Gaussian process regressor, Upper Confidence Bound, cross-correlation, adaptive sensing, optimal sensor set, temporal correlation

1.0 Introduction

The evolution of the Internet of Things (IoT) technology took over the industries by connecting millions of devices that are used in our lifestyles. To sense and monitor the parameters of the habitat, IoT node sensors have tremendous applications in growing at a significant rate. Wireless sensor networks (WSN) have numerous sensor nodes to monitor the environmental parameters. A massive number of sensor nodes are connected wirelessly to the base station or an edge node that constitutes WSN. WSNs are widely used in many industrial applications such as health care, border surveillance etc... Good quality sensors consume more power along with good accuracy of the sensed signal. Hence the energy replenishment of the nodes is a major concern. In such scenarios, the large emplacement of these sensor nodes is very challenging. The energy consumption of nodes directly depends on sensing and transmission. Nowadays, good quality sensors with utmost accuracy consume more sensing power than transmission power. To reduce the problems associated with it by increasing the efficiency of WSN by some intelligence-based sensing. Hence the energy consumption of sensors is reduced by the presented adaptive sensor selection framework. The framework exploits the correlation among the parameters and the temporal correlation of the sensing parameters and sends it to the edge node for receiving the feedback mechanism from the nodes to adapt to the system parameters. The presented framework reduces both the sensing and transmission power by 54% with a minimum prediction error that is with an MRE of 1%

1.1 Literature review

Numerous studies discussed sensing energy efficiency which can be split into two categories. They are

- Adaptive sampling approach on individual parameter node single-handedly
- Selection of active sets premised on the spatio-temporal correlation

Both these kinds reduce the volume of data and consumption of energy in transmission and sensing. In [1], three adaptive sampling algorithms are presented for node-level analysis. They are

- Anova and Bartlett test

- Jaccard Similarity function
- Euclidean Distance function

These functions are used to determine the sampling interval based on the previous samples collected by the sensors

The work in [4], is sparse Bayesian Learning (SBL) premised on adaptive sensing where some of the sensors in the network connected wirelessly are selected for a measurement period based on correlations of spatio-temporal values among the sensing signal vectors. In general, sensor nodes consist of single sensors to monitor the environmental parameters in the environment. To elevate the energy efficiency of the densely organized sensor node hubs, an adaptive selection of sensor framework is presented in [4]. This exploits the correlations of spatio-temporal values and cross-correlations among the parameters to find the optimal number of the sensor to be actuated in the next measurement period. The compressing algorithm in paper [5], selects a few sensor nodes from the huge set in a miscellaneous sensing environment

The Gaussian Process Regression (GPR) based model in [6], is presented to predict the spatio-temporal parameters of the portable sensor network. GPR can predict with a good amount of accuracy according to [7] and [8]. The works in [9], considered real-time scenarios where data collected are immediately transferred to the sensor hub to observe the system state.

The presented approach in [2], works based on an adaptive sampling algorithm by the Nyquist criteria to find the rate of sampling at which the samples are to be collected to reduce the bandwidth energy. The Nyquist criteria give you the maximum observed frequency of the sensed signal of all parameters. By that, the sampling rate of all the sensed parameters is sampled at the same rate. The presented multi-parameter sensing framework is modelled as a Multi Arm Bandit (MAB) problem which exploits the correlation of the sensing habitat parameters at a node to actuate the sensors online. This framework introduces the reinforcement-based learning approach to make the sensors active based on the correlation of the parameters, energy consumption of sensors, and the availability of energy at the node. This activation is made possible by the discounted Upper Bound Confidence (UCB) algorithm. The reward needs to be calculated for every measurement cycle since the environment is dynamic. The rewards are drawn from the unknown Gaussian distribution. The length of the data collection span or the measurement period is adaptive to the dynamic process, which innately exploits the variation of correlation of the sensing process. This is achieved by the mapping function of parameterization that maps the cross-correlation variation to the subsequent measurement period. Through this,

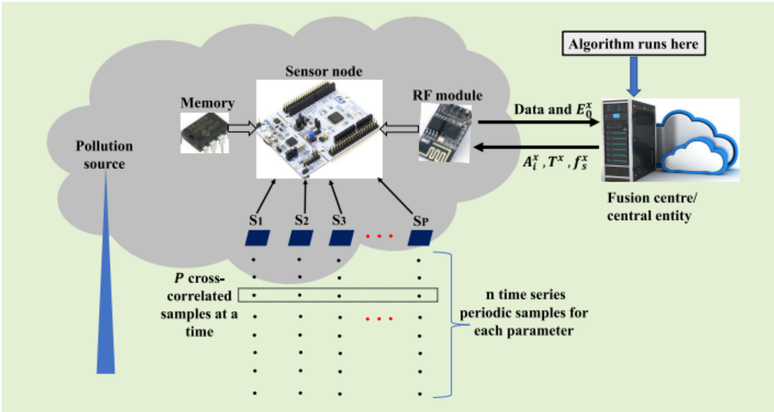


Figure 1.1: Process flow of framework [2]

the linear measure of the measurement period is made adaptive. Gaussian Process Regression (GPR) model is used to predict the data of the inert set sensors at the central entity based on the cross-correlation of the parameters.

1.2 Adaptive sensor selection framework

1.2.0 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

1.2.1 System model

The sensor hub consists of 7 sensors, monitoring each sensing parameter in the environment. In the x^{th} data collection interval, the data sensed at the instant of sampling is denoted as

$$Z^x = y^x + \eta^x \tag{1.1}$$

where $Z^x \in \mathbb{R}^{P\times 1}$ is the measurement vector containing all the observed parameters in the environment. y^x is the actual vector signal and the η^x is the noise accompanied along by the actual signal vector where the noise is considered as additive Gaussian, independently and identically distributed with zero expectation and σ^2 variance. Z^x is the matrix that contains the temporal measurements of all monitored habitat parameters. The sensors deployed in the environment sense the spatio-temporally varying signals which exhibit cross-correlation among the sensing parameters which predicts the system from the cross-correlated parameters. There are 2^7 possible combinations of sensors from which active sets are figured out based on the correlation of the parameters, consumption of energy by the sensors and the availability of energy at the node. In a collection interval x if A_i^x denotes the set of all active sensors and the corresponding inactive set of sensors be $B_i^x = P - A_i^x; 1 \leq i \leq N$. Therefore, $A_i^x = \{P_{A_i^x,m}; 1 \leq m \leq A_i^x\}$ and $B_i^x = \{P_{B_i^x,k}; 1 \leq k \leq B_i^x\}$. Let S be the set which contains all the active and the sleep subsets of sensor nodes, ie $S^x = \{(A_i^x, B_i^x); 1 \leq i \leq N\}$

1.2.2 GPR based predictive model

To predict the parameters of the sleep set, Gaussian Process Regressor (GPR) is used. Gaussian Process Regression assumes prior the data sets that fit well with the actual sensing vector signals at the node. Gaussian Process Regression doesn't have any parentric form which makes the model flexible to predict the correlated parameters from the active set of sensors. It gives 95% confidence bound on the predicted signal. Let Z be the complete matrix of an n-sized feature of vector signals and y be the target signal vector containing the target values of n from the set of training data, and w be the weight of the vector. The prior of the test input (z*) is given by

$$Prior : Pr(f(z*)) = \int Pr\ (f|w, (z*))\ Pr\ (w)\ dw \tag{1.2}$$

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

$$Posterior : Pr(f(z*)|Z, y) = \int Pr\ (f|w, (z*))\ Pr\ (w|\ Z,\ y)\ dw \tag{1.3}$$

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

Training the n models to predict n parameters from the correlated parameters of active sets by the GPR model that includes a kernel or covariance function. The kernel function that is used to predict the parameters consist of a composition of the linear kernel and Radial Basis Function kernel with the specified bound based on the correlation of the parameters. This kernel function along with the Gaussian Process Regressor produces the trained models by fitting the training data to the n model for n predicted parameters.

1.2.3 Discounted UCB algorithm

The presented adaptive selection framework accounted for a node-level approach to select the optimal active sensor sets in a sensor hub that monitors multiple parameters. Let the correlation threshold be $c_t h$. If the parameters a and b correlate greater than $c_t h$, they are said to be correlated. For every correlated parameters of subset $(A_i^x, B_i^x) \in S^x$, the expectation of cross-correlation between the parameters A_i^x and B_i^x is:

$$C_i^x = \frac{1}{B_i^x} \Sigma_{k=1}^{B_i^x} \frac{1}{c_{i,k}^x} \Sigma_{q=1}^{c_{i,k}^x} |c^x(q,k)|; \forall k \in B_i^x \quad and \quad q \in \hat{C}_{i,k}^x \tag{1.4}$$

$\hat{C}_{i,k}^x$ be the set which contain the parameters of A_i^x highly correlated with k^{th} parameters of B_i^x. C_i^x is defined as a cross-correlation component implying a correlation between A_i^x and B_i^x
Energy consumption for the active sets A_i^x can be given by

$$E_i^x = \Sigma_{m=1}^{A_i^x} En_m^x; \forall m \in A_i^x \tag{1.5}$$

En_m^x is the energy consumed for sensing by the m^{th} sensor.
The prediction error rate for the subset B_i^x is:

$$PE_i^x = \frac{1}{B_i^x} \Sigma_{k=1}^{B_i^x} Pe_k^x; \forall k \in B_i^x \tag{1.6}$$

Pe_k^x is the error of prediction for the k_{th} parameter in B_i^x. C_i^x and PE_i^x are dynamic, but E_i^x does not vary since the energy consumption of sensors is fixed in sensing.
Upper Confidence Bound (UCB) algorithm is a prominent cost-based reinforcement learning method that is used for solving Multi-Armed Bandit (MAB) problems, where the resolution of selecting the online sensor set is based on the preceded experience it has gained. The objective is to reduce regret by escalating the reward achieved by selecting an optimal set. The reward is given by

$$R_i^x = \frac{\lambda^x \left(C_i^x\right)^\gamma}{\nu^x \left(E_i^x\right)^\beta} \tag{1.7}$$

where $\lambda^x \cong \frac{E_0^x}{E_{batt}}$ is the regularized energy available at the node and $v^x = \max_{i \in S^x} \frac{(C_i^x)^\gamma}{(E_i^x)^\beta}$ Here, the reward is confined between [0,1]. A greater value of C_i^x means the quality of sense is better. If C_i^x is greater than c_{th} , for a few sets $i \in S$, the corresponding inert sets are correlated from which we can ensure the staunch reconstruction of signals. Here β and γ are the charged weight to direct C_i^x and E_i^x in the reward. The values of β and γ will lessen the regret. The empirical mean for reward distribution is given by

$$\hat{\mu_i^x} = \frac{1}{x}\Sigma_{t=1}^{x} \frac{\lambda^t \left(C_i^t\right)^\gamma}{v^t \left(E_i^t\right)^\beta} \tag{1.8}$$

The objection function to choose the optimal online sensors at the (n+1) measurement period is given by

$$A_i^{x+1} = \max_{i \in S_x} \frac{1}{x}\Sigma_{t=1}^{x} \frac{\lambda^t \left(C_i^t\right)^\gamma}{v^t \left(E_i^t\right)^\beta} + \sqrt{\frac{2 \ln \frac{1}{\partial}}{T_i^x}} \tag{1.9}$$

with constraint $C_i^x > c_{th}$ and $I^{(x+1)} E_i^{(x+1)} < E_0^x$ For every optimal sensor set, C_i^x is restored for every measurement period where E_i^x remains unaltered due to its fixed consumption of energy. $I^{(x+1)}$ be the count of collected samples in the $(x+1)^{th}$ period for each parameter. T_i^x is the actual count of the i^{th} online sensors activated and ∂ denotes the confidence bound.

1.2.4 Adaptive measurement cycle

Transmission of data drains larger notable power. In a period, correlation among the observed parameters of sensing varies very slowly. By considering this, the sampling rate at which the signal to be sampled is decided, stored in the database and transmitted after a period known as the measurement period or the data collection span. Let the length of x^{th} measurement period be T^x. The data collection is made adaptive by using a mapping function based on parameterization formulated in [2] where the correlation changes in the x^{th} and $(x+1)^{th}$ measurement cycle are given by

$$y(d) = a_0 + a_1 (d)^\alpha \; (cycle/hr) \tag{1.10}$$

$$d = \frac{1}{N}\Sigma_{i=1}^{N} \left|C_i^x - C_i^{x-1}\right| \tag{1.11}$$

where d is the mean difference between the previous and present correlation factors in the set S and y(d) is the frequency of the measurement period or data collection span in cycle/hr The length of the measurement period is given by

$$T^x = \frac{1}{y\,(d)} \tag{1.12}$$

Here α is the shaping parameter that determines the rate of adaption. a_0 and a_1 can be calculated with the boundary conditions: $d \in [0, 1]$ for $y(d) \in [b_0, b_1]$ where b_0 and b_1 are user-defined. The sampling rate of each sensor depends on the Nyquist criteria where the maximum frequency of the observable parameters is set as the Nyquist rate to sample all the parameters of the active sets. Due to the dynamics of the environment, the sampling frequency change in every measurement cycle.

1.2.5 Algorithm

- Collect the sampled data of all the parameters from the sensors for a given period and train the Gaussian Process Regressor model. The optimal samples collected to train the model are between 1500 - 1600.
- Construct the design matrix S^x to calculate C_i^x and E_i^x using 1.4 and 1.5
- Find the optimal online sensor sets A_i^x by solving 1.9
- Find the maximum frequency (f_m^x) of the signal parameters using power spectral density from FFT
- Find the Nyquist sampling rate by detecting the maximum observable frequency and it is given by $f_s = 2 * max(f_m^1, f_m^2, f_m^3 \ldots . f_m^p)$
- Calculate the predicted error $PE_i^x; \forall i \in S$ using 1.6
  - If $PE_i^x - PE_i \leq \varepsilon_i; \forall i \in S_x$
    Calculate $y(d)$ and T^x from 1.10 and 1.11
  - else
    Find the length of the measurement cycle from the Nyquist rate and it is given by $T^x = \frac{n}{f_s}$. Jump to step 1 to retrain the GPR model
- The measurement cycle is incremented to 1

Input: Sampled data of all parameters and E_0^x from the sensor node with flags $e = 0$ and $e' = 1$

if $e = 1$ **then**

  Train and validate the Gaussian Model from the recently collected samples

  Determine $PE_i; \forall i \in S$ using 1.6

  Set $x = 0$, $e = 0$, and $T^x = T'$

else

  if $e' = 1$ **then**

    Find $PE_i^x; \forall i \in S$ using 1.6

    if $|PE_i^x - PE_i| <= \varepsilon_i; \forall i \in S_x$ **then**

      Evaluate y(d) from 1.10 and 1.11

      Set $T^x = \frac{1}{y(d)}$

      Set $e' = 0$

    else

      Set $e' = 0$ and $e = 1$

      Determine maximum frequency $f_m^p; \forall p \in P$ using FFT

      Set $f_s = 2 * max(f_m^1, f_m^2, f_m^3.....f_m^p)$

      Set $T^x = \frac{n}{f_s}$

    end

  else

    Predict the inert samples of the sleep sets using the trained model of GPR

    Evaluate y(d) from 1.10 and 1.11

    Set $T^x = \frac{1}{y(d)}$

    Find $ct_p^x; \forall p \in P$

    while $ct_p^x < ct_{p,th}; \forall p \in P$ **do**

      Set e' = 1

    end

  end

end

while $e = 0$ **do**

  Build S^x and solve C_i^x and $E_i^x \forall i \in S^x$ using 1.4 and 1.5

  Find optimal active sensor sets A_i^x by solving 1.9

  Find maximum frequency $f_m^p \forall p \in P$ using FFT

  Set $f_s = 2 * max(f_m^1, f_m^2, f_m^3.....f_m^p)$

end

Set $x = x + 1$

Output: Transmit T^x,f_s^x, A_i^{x+1}, e, e' to the node

- Transmit updated T^x,f_s^x, A_i^{x+1}, e, e' send back to the sensor nodes for the operation of next measurement period.
- In the next measurement period, samples from the active set of sensors reach the base station. The sleep set parameters are predicted from the trained GPR model.

1.3 Implementation of Adaptive Framework

1.3.0 Experimental setup

The performance is analyzed based on observational and simulational results. To feature the efficiency of the adaptive framework, Air Pollution Monitoring Device (APMD) is deployed on the IIT Delhi campus to fetch the data samples.

Table 1.1: Sensor specification [2]

Sensors	Parameters	Energy consumption (J)
DHT11	Temperature and Humidity	12m
MQ-137	NH3	1.1
AFE-A4 alphasense	NO2, Ozone, CO, SO2	54m
Alphasense OPC N3	PM_{10}, $PM_{2.5}$	29.55

The APMD sensor node consists of seven sensors to observe nine parameters in the environment. Four gas monitoring sensors (NO2, Ozone, CO, SO2) are embedded in a 3rd sensor board, energized by the main supply which makes it challenging to determine the energy consumption of specific sensors. The distinctive energy consumption of these sensors is $1.57J, 0.054J, 0.642J, and 1.35J$.

Figure 1.2: Hardware Setup of APMD with solar panel

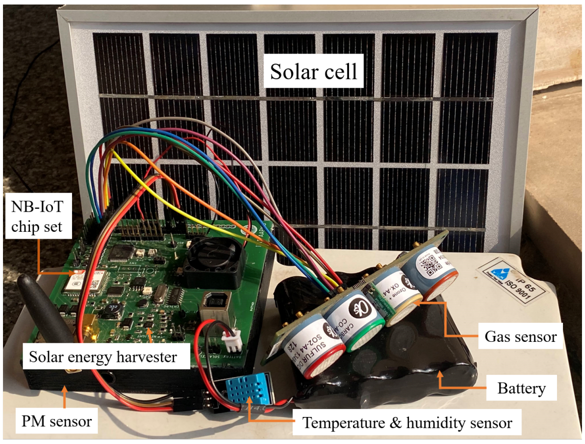


Figure 1.3: Hardware components of APMD

The cross-correlation is exploited from the collected samples of all the deployed sensors that return the active set of sensors to be activated in the subsequent measurement period and the remaining parameters are predicted from the trained model using the Gaussian Process Regression model. The simulational results given in the next subsection substantiate the predicted values to that of the actual true values and give the mean relative error of less than 1%. This makes sure that the predicted values can be reconstructed with minimal sensing error.

1.3.1 Results and discussions

In each measurement cycle, various active sensors get activated based on the correlation of the parameters, energy consumption of the distinctive sensors and the availability of energy in the node. The correlation threshold is fixed as $c_t h = 0.5$ since it gives maximum reward in the discounted UCB algorithm than the others. The above threshold is fixed based on the observation of the maximum of the calculated rewards for each of the correlation factors.

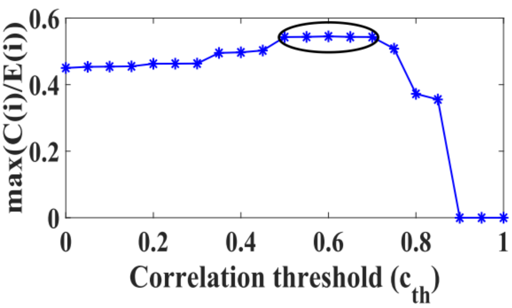


Figure 1.4: Optimum correlation threshold [2]

The selection of training samples needs to be in such a way that the trained model neither underfit nor overfits the test samples. This selection of optimum samples is made in a trial and error until the model starts to overfit the data. This is a kind of exploration in terms of machine learning. The reduction in the prediction error gives the most accurate reconstructed signal for the predicted parameters. The optimum training length sequence is 1500 – 1600 [2] assuming that the trained models meet well with minimal train and test error.

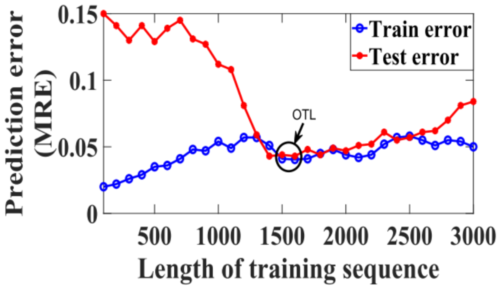


Figure 1.5: Optimum training samples [2]

The Mean Relative Error (MRE) is to validate the trained model for the prediction of sleep set sensors and it is given by

$$MRE_p = \frac{1}{L}\sum_{k=1}^{L}\frac{|actual - predict|}{actual} \tag{1.13}$$

where L be the total samples collected at each measurement period
The mean error of reconstruction for P parameters at the x_{th} measurement period is given by,

$$RE^x = \frac{1}{P}\Sigma_{p=1}^{P} MRE_p^x \tag{1.14}$$

where MRE_p^x is the error of reconstruction for the p_{th} parameter at the x_{th} measurement period. To obtain the energy effectiveness of the presented adaptive sensor selection framework, the consumption of energy sensing at the sensor hub node is compared assuming the sensor node is battery utilized. Let E_a^l and E_p^l be the energy of sensing for all parameters with that of the active sensor set energy up to l measurement cycles. The average energy saved in l measurement cycle by activating the optimal active sensors is calculated in terms of percentage and it is given by

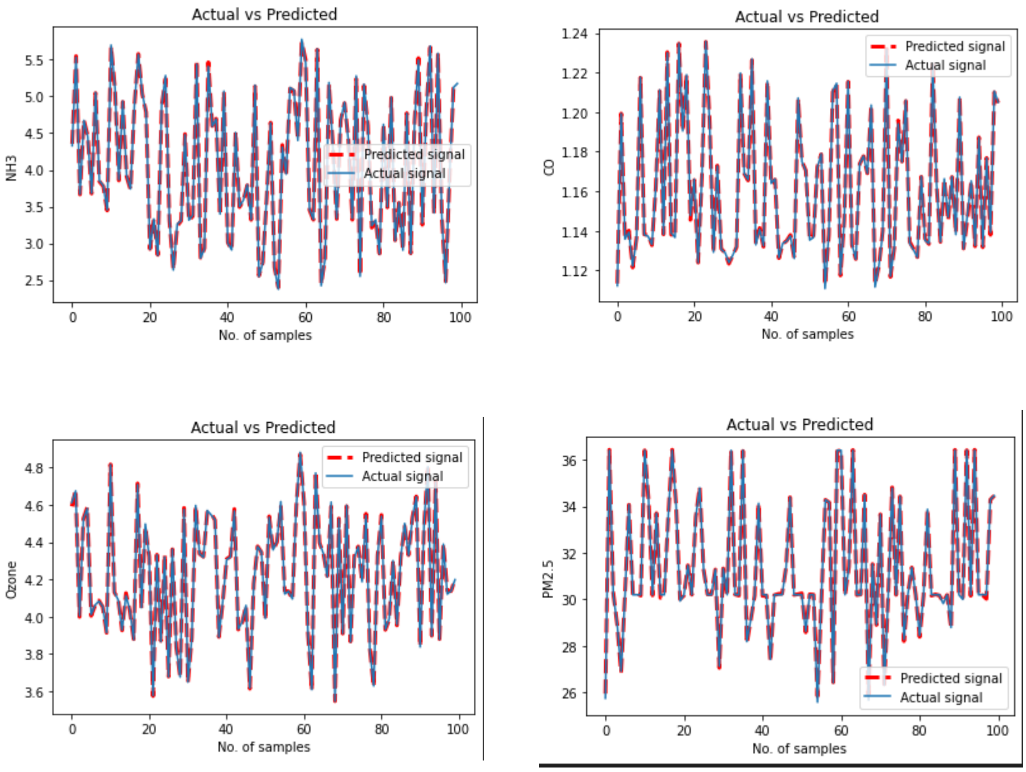
$$Energysaved = [\frac{1}{L}\Sigma_{l=1}^{L}\frac{E_a^l - E_p^l}{E_a^l}] * 100 \tag{1.15}$$

The energy efficiency is compared with that of the Anova model by varying the correlation threshold. For $c_t h = 0.7$, the presented adaptive selection framework is 46% energy effective[2] compared to the Anova model adaptive sampling algorithm. By considering the Mean Relative Error is in the acceptable range of (1%), the presented adaptive sensor selection framework with $c_t h = 0.5$ saves 54% energy consumption[2] more than that of the Anova model.

1.3.2 Outputs

Sci-kit is a free source available online to train machine learning models. The generated models for the operation of APMD in edge node are implemented through the Gaussian Process regressor model using the composite kernel function and the input is in anisotropic form. From this composite function, the model is trained through the k-fold cross-validation method to find the optimized kernel to fit the training samples. The training needs to be done neither the model underfit nor overfit the training samples. Thus the obtained optimized training models are used to predict the correlated parameters of sleep sets for the measurement cycle.

The following are the outputs generated in python implemented through the sci-kit library. The presented figures are the predicted sleep set parameters for a measurement cycle and it is validated with the actual test signal parameters



The reconstructed signal follows exactly the actual test signals which show a good amount of prediction rate which is generated by taking the optimum train samples to train the model of GPR.

The validation is carried out for 10 measurement periods using the trained GPR model and the corresponding readings of the mean relative error, normalised mean square error, energy efficiency and the residual energy of the multi-parameter sensor hub are noted down. From that, the reconstructed signal inferred the mean relative error is less than 1% which is a good accuracy in predicting the sleep set parameter signal with a convenient amount of energy saving in the multi-parameter sensor hub.

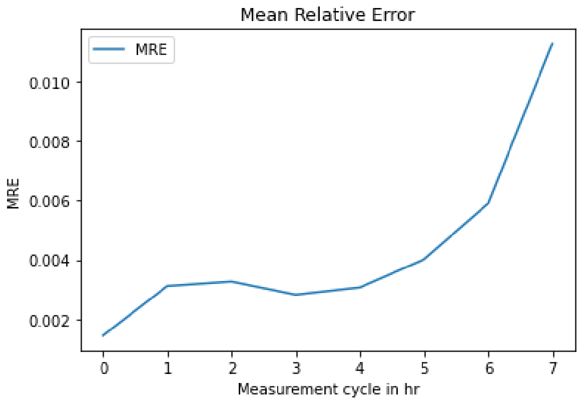


Figure 1.6: Mean relative error

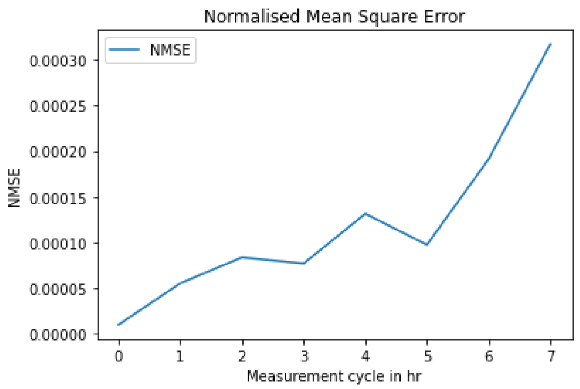


Figure 1.7: Normalised mean square error

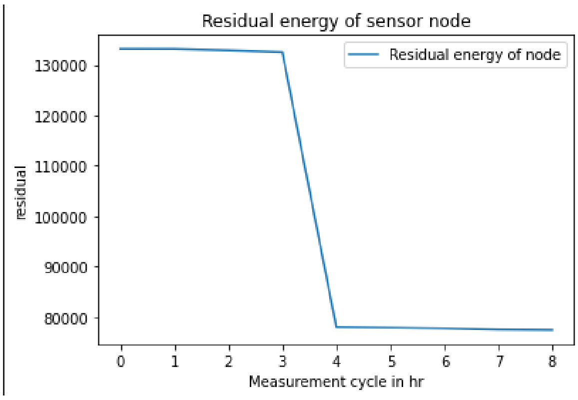


Figure 1.8: Residual energy of node

1.4 Conclusion

In a process dynamic environment, learning the system of parameters with all precedent experience gained gives more insight into the process dynamics of the parametric system. From the presented Adaptive Sensor Selection Framework, the optimal online set has been figured out by resolving the trade-off between several correlated parameters in the environment using discounted UCB algorithm. Considerable simulational studies carried out in the implementation of the framework in APMD (Air Pollution Monitoring Device) have validated the effectiveness of this presented approach. The presented method gives the optimal set of sensors based on the correlation of parameters in the dynamic environmental habitat along with energy efficiency in consumption.

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