CEG5103/EE5024 Case Study

Machine Learning (ML)-based Air Quality Monitoring using Vehicular Sensor Networks

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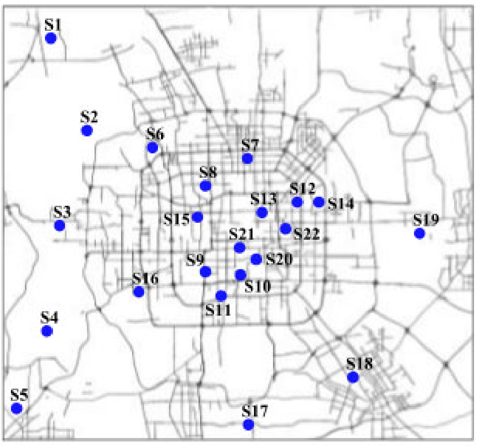
IEEE ICPADS 2017, Shenzhen, China

Dec. 17, 2017

Presentation Outline

1. Introduction to Urban Air Quality Monitoring
2. Our Proposed Algorithm
3. Conclusions

Conventional Stationary Monitoring Network



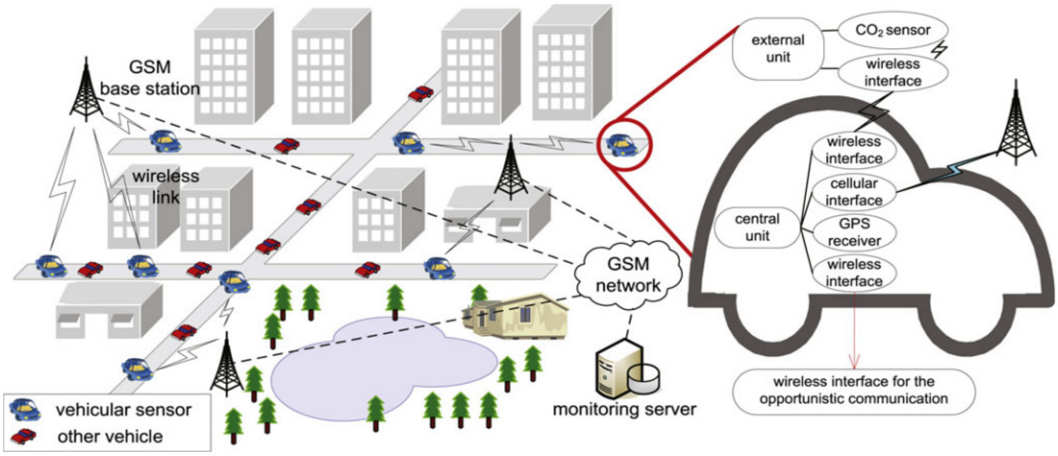
A) Configuration of a station B) Air quality measurement stations in Beijing

- Air quality is a major concern in modern cities
- To monitor the air quality in a city, important air quality parameters such as CO, $PM_{2.5}$ need to be collected

Static Monitoring Stations:

- Can accurately measure a wide range of air quality parameters
- Require a big land area, high cost (about USD 200,000 for construction and USD 30,000 per year for maintenance)
- Non-scalability for changes in urban arrangement, activities or regulation, which require relocating stations or adding new stations

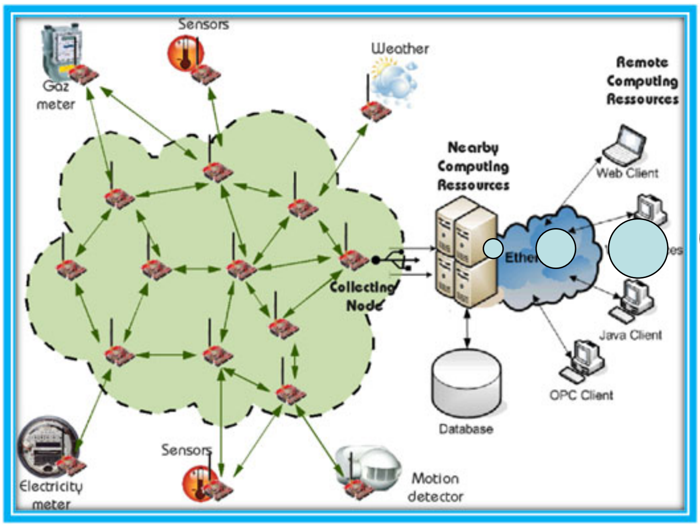
Air Quality Monitoring using Vehicular Sensor Network



Source: S. C. Hu *et al.* "A vehicular wireless sensor network for CO2 monitoring," in Proc. 2009 IEEE Sensors

- Vehicular sensor network (VSN) is an efficient solution for the urban air quality monitoring
- Formed by group of vehicles (e.g., cars, buses) which are equipped with computing units and sensing devices
- Vehicles move around the city area and measure air quality parameters

System Model



Build a global sensing map over a monitoring area based on the collected sensing data

Existing Centralized Method:

- Sensing vehicle sends all its collected data to the monitoring center
- The center builds the sensing map by utilizing the collected sensing data
- Main disadvantage is the high communication cost for transmitting the data from the vehicles to the center

Spatial Interpolation Methods

- Normally, spatial interpolation methods are used to predict the air quality at unsampled location
- In general, the value z at unsampled location x_0 are interpolated based on values of sampled ones [1]

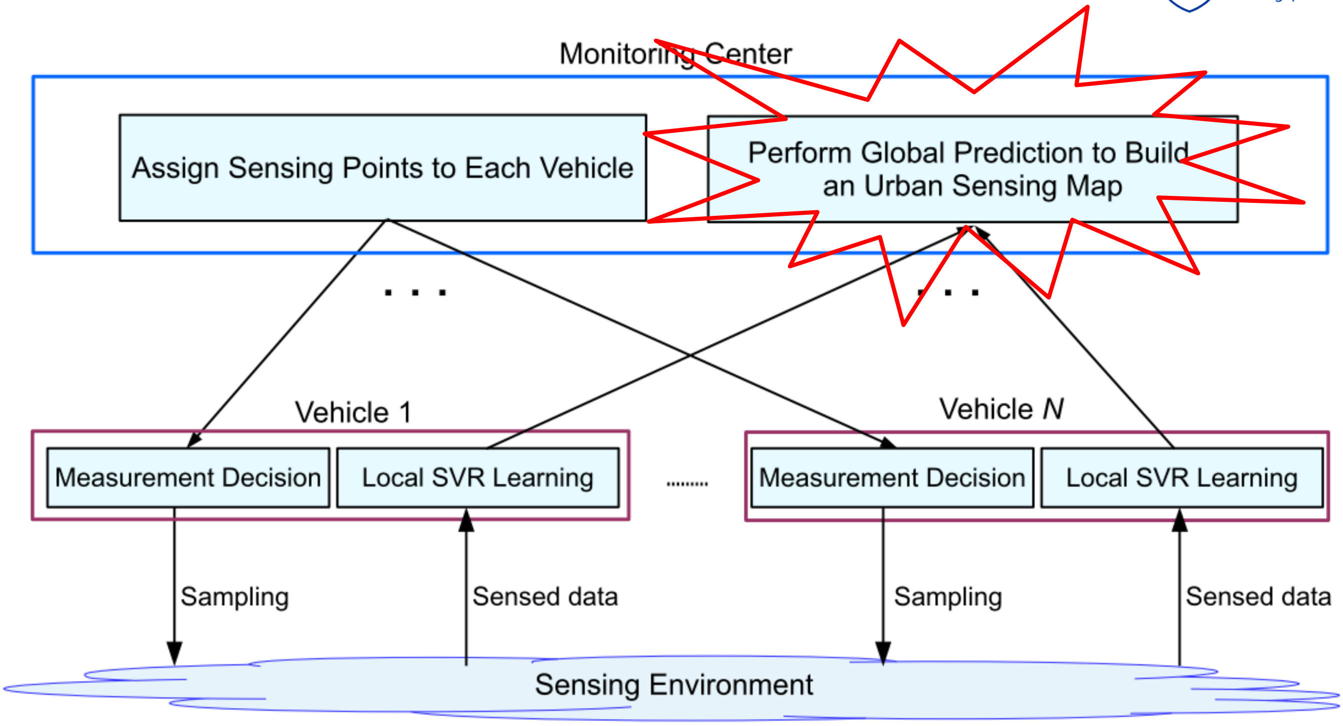
$$z(x_0) = \sum_{i=1}^{n} \omega_i z(x_i) \ and \sum_{i=1}^{n} \omega_i = 1$$

where ω_i represents the weights assigned to each of sampled locations.

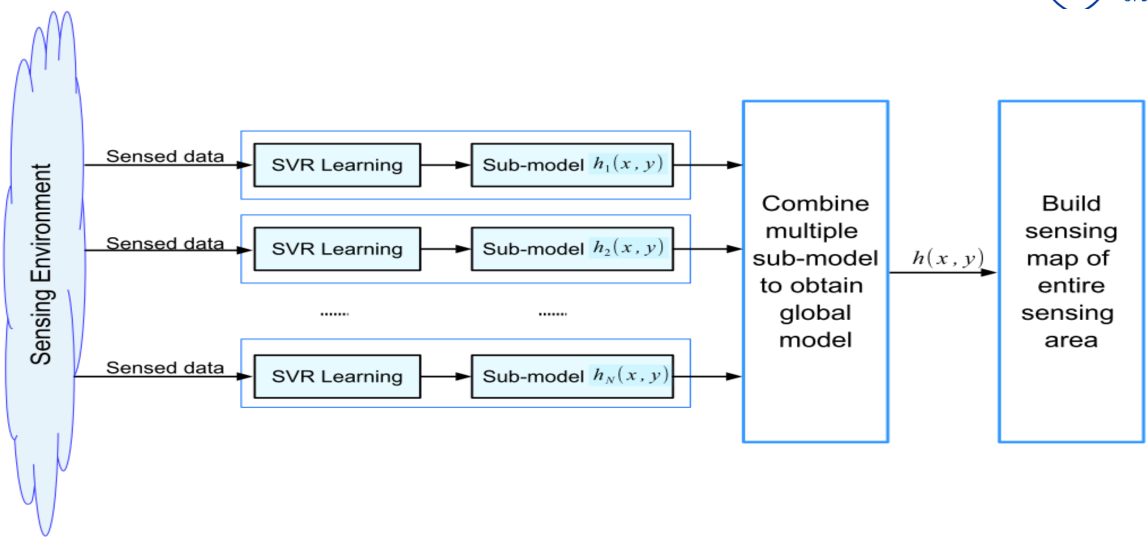
- Depending on the way of determining the weight value ω_i, three interpolation methods are widely used:
  - Nearest Neighbor (NN): take the value of the sampled point which is the nearest to x_0
  - Inverse Distance Weighting (IDW): assign a higher weight for the closer sampled point.
  - Kriging: use a variogram to compute the weight which minimizes the variance of the estimated value

[1] Wong DW, Yuan L, Perlin SA, "Comparison of spatial interpolation methods for the estimation of air quality data", J Expo Anal Environ Epidemiol, 2004;14(5):404–415.

MLAirM: Machine Learning (ML)-based Distributed Air Quality Monitoring Scheme



Building a Global Sensing Map based on Distributed Machine Learning



- Each vehicle is assigned to take measurements on a set of points then build a local sensing map using support vector regression (SVR) model
- After a sensing period, all vehicles will sends local model parameters to the center.
- Then, the center uses the received models to build the entire sensing map of the interest area.
- Communication cost is reduced since vehicles do not need to send raw sensing data to the center

Distributed Support Vector Regression (SVR)

- Each vehicle constructs its SVR sub-model using its collected data:

$$f(x) = \langle w, x \rangle + b \text{ with } w \in \mathcal{X}, b \in \mathbb{R}$$

mapping function $\varphi(x)$

$$\text{minimize} \quad \frac{1}{2}\|w\|^2$$

$$\text{subject to} \quad \begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon \\ \langle w, x_i \rangle + b - y_i \le \varepsilon \end{cases}$$

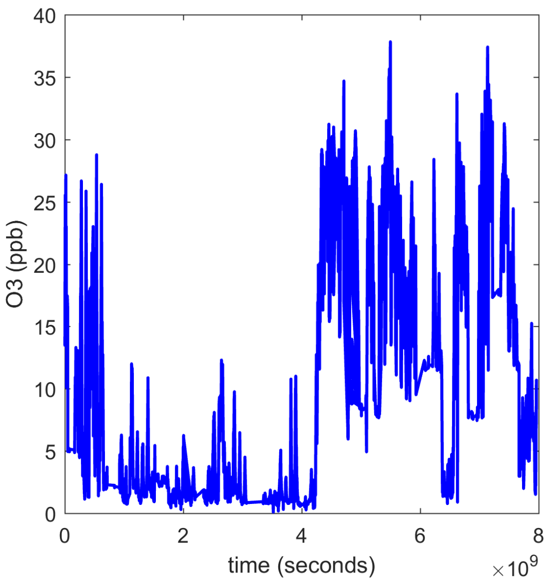
- The center uses a fuzzy synthesis[2] method to predict the measurement y at location x, based on the predicted value y_i of N vehicles' sub-models

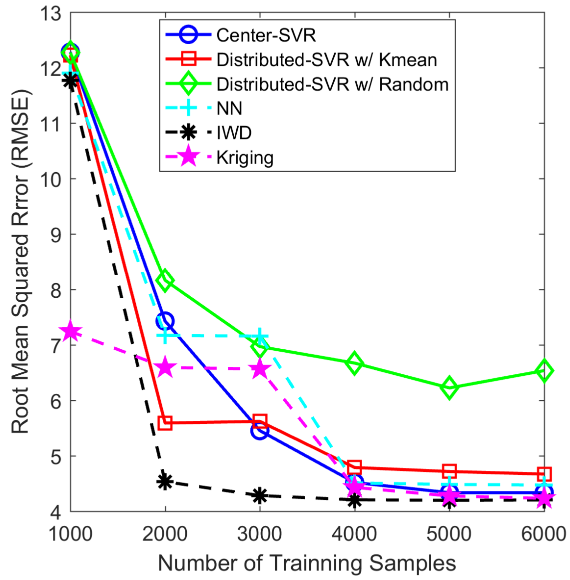
$$y = \sum_{i=1}^{N} \eta_i \, y_i \text{ where } \begin{cases} \eta_i = 1, \eta_{j \neq i} = 0, & \text{if } d_i = 0 \\ \eta_i = \dfrac{\frac{1}{d_i}}{\sum_{i=1}^{N} \frac{1}{d_i}}, & otherwise \end{cases}$$

where $d_i = \|x - c_i\|$, c_i is the center of i[th] subset of samples of sub-model i

[2] J. Cheng, J. Qian, Y. Guo, "A distributed support vector machines architecture for chaotic time series prediction", Proc. Neural Inform. Process, 2006.

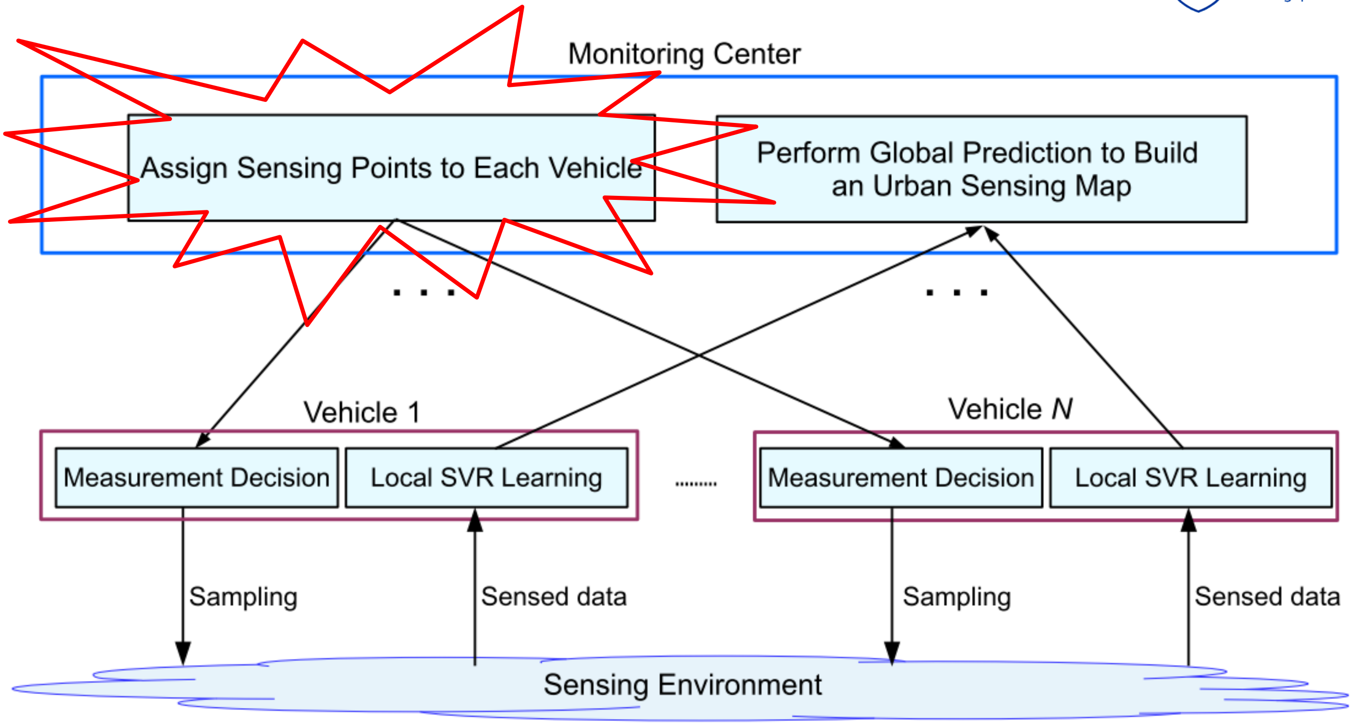
Motivating Example



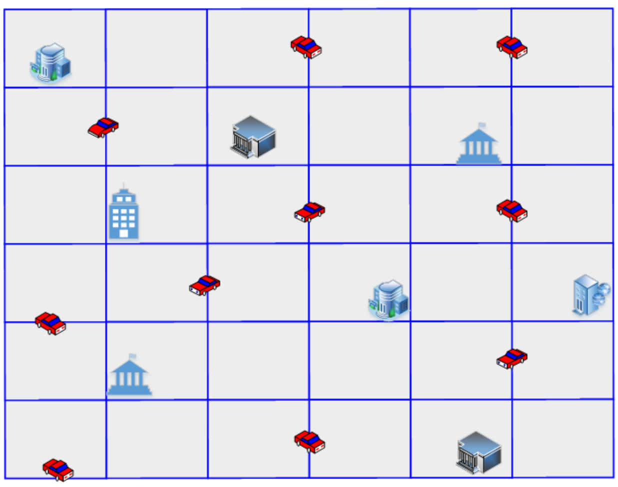


- Use the air quality data, which is collected by a tram in the city of Zurich at different locations over time in **OpenSense** project conducted by researchers at ETH Zurich

Our Proposal: Machine Learning (ML)-based Distributed Air Quality Monitoring Scheme



How to Assign Sensing Locations to Vehicles



An Urban Area of Interest

- Denote $\mathrm{V} = \{1, 2, \ldots, N\}$ as set of vehicles.
- The area is divided into grid of L square sub-areas as $\mathbb{L} = \{1, 2, \ldots, L\}$.
- The measurement which is taken at any location inside the sub-area indicates the sensing value of the cell.
- Each vehicle has a different probability to visit a sub-area during the sensing duration

Main objective is to assign L sub-areas to N vehicles such that the probability that every sub-areas is sensed with the required number times while the prediction error is minimized

Quality of Information Requirements

- Denote m_l as number of different measurements required to take in a sub-areas l to capture the sensing value variation.
- The value of m_l can be determined as the required number of samples to capture 95% of the observed variability with standard deviation (σ) and an accepted error (e) as

$$m_l = \left(1.96\frac{\sigma_l}{e}\right)^2$$

- Denote $\mu_{il}\ (i = 1, \ldots, N; l = 1, \ldots, L)$ as the expected number of measurements that the vehicle i can take at the cell l during the sensing period.
- The value of can μ_{ij} be estimated using the vehicle's trajectory history.

Successful Measurement Probability Aware Location Assignment (SMP-LA)

- Denote x_{il} as a decision variable which is equal to 1 if the sub-area l is assigned to the vehicle i. Otherwise, it is zero.
- Main objective is to maximize value of function F_i on each set of points assigned to vehicle i

$$F_i = \underbrace{\beta_1\left(\sum_{l=1}^{L} P_{il}x_{il}\right)}_{\text{probability of successfully taking a number of required measurements}} - \underbrace{\beta_2\sum_{l=1}^{L-1}\sum_{k=l+1}^{L} x_{il}x_{ik}d_{lk}^2}_{\text{sum of squared inter-cluster distances of assigned points}}$$

where

- d_{lk} is distance between sub-areas l and k
- $\frac{\mu_{il}}{m_l}$ is probability that vehicle i can take m_l number of measurements required in sub-area l
- $P_{il} = \min(1, \frac{\mu_{il}}{m_l})$

SMP-LA: Optimization Formulation

- Main objective is to maximize value of function F_i on each set of points assigned to vehicle i

$$F_i = \beta_1 \left(\sum_{l=1}^{L} P_{il} x_{il} \right) - \beta_1 \sum_{l=1}^{L-1} \sum_{k=l+1}^{L} x_{il} x_{ik} d_{lk}^2$$

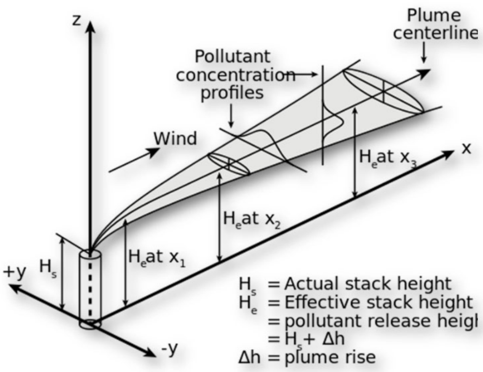
- The optimization problem is formulated as

$$\begin{aligned} & \max \min(F_i, \ldots, F_N) \\ \text{s.t.} \quad & \sum_{i=1}^{N} x_{il} = 1 \qquad && l = 1, \ldots, L \\ & x_{il} \in \{0, 1\} && i = 1, \ldots, N,\ l = 1, \ldots, L \end{aligned}$$

- To linearize the product of two binary variables, we introduce $z_{lk}^i = x_{il} x_{ik}$ and some additional constraints as $z_{lk}^i \leq x_{il} + x_{ik}$

Performance Evaluation

- Use the T-Drive dataset which contains trajectories of 10,357 taxis travelling in the city of Beijing over one week
- Third Ring Road of Beijing is selected as a sensing area which is divided into L = 40,000 (200×200) sub-areas
- To simulate air pollution in the sensing area, we adopt the Gaussian plume equation to calculate the pollutant concentration of downwind position (x, y, z) as

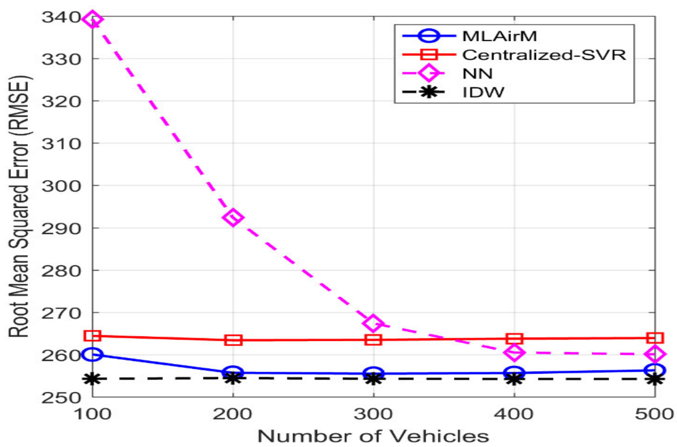


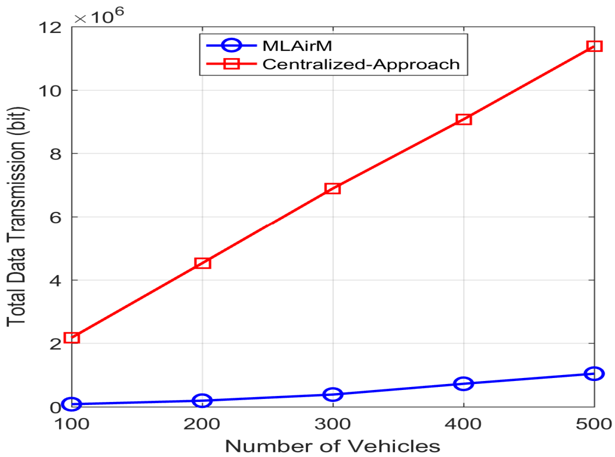
$$C(x, y, z) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right)\left[\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right]$$

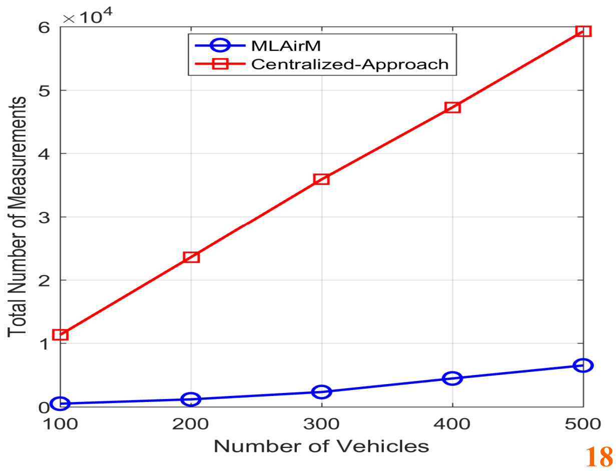
Performance Evaluation

- Evaluate the performance of following algorithms:
  - MLAirM: our proposed scheme = distributed SVR + optimal sensing location assignment
  - Centralized approaches:
    - Centralized-SVR
    - Nearest Neighbor (NN)
    - Inverse Distance Weighting (IDW)
- Performance metrics:
  - Root mean squared error (RMSE): between predicted and accuracy measurements at all sub-areas in the monitoring area.
  - Total data transmission: total number of bits transmitted from all vehicles to the center
  - Total number of measurements: total number of measurements taken by all vehicles

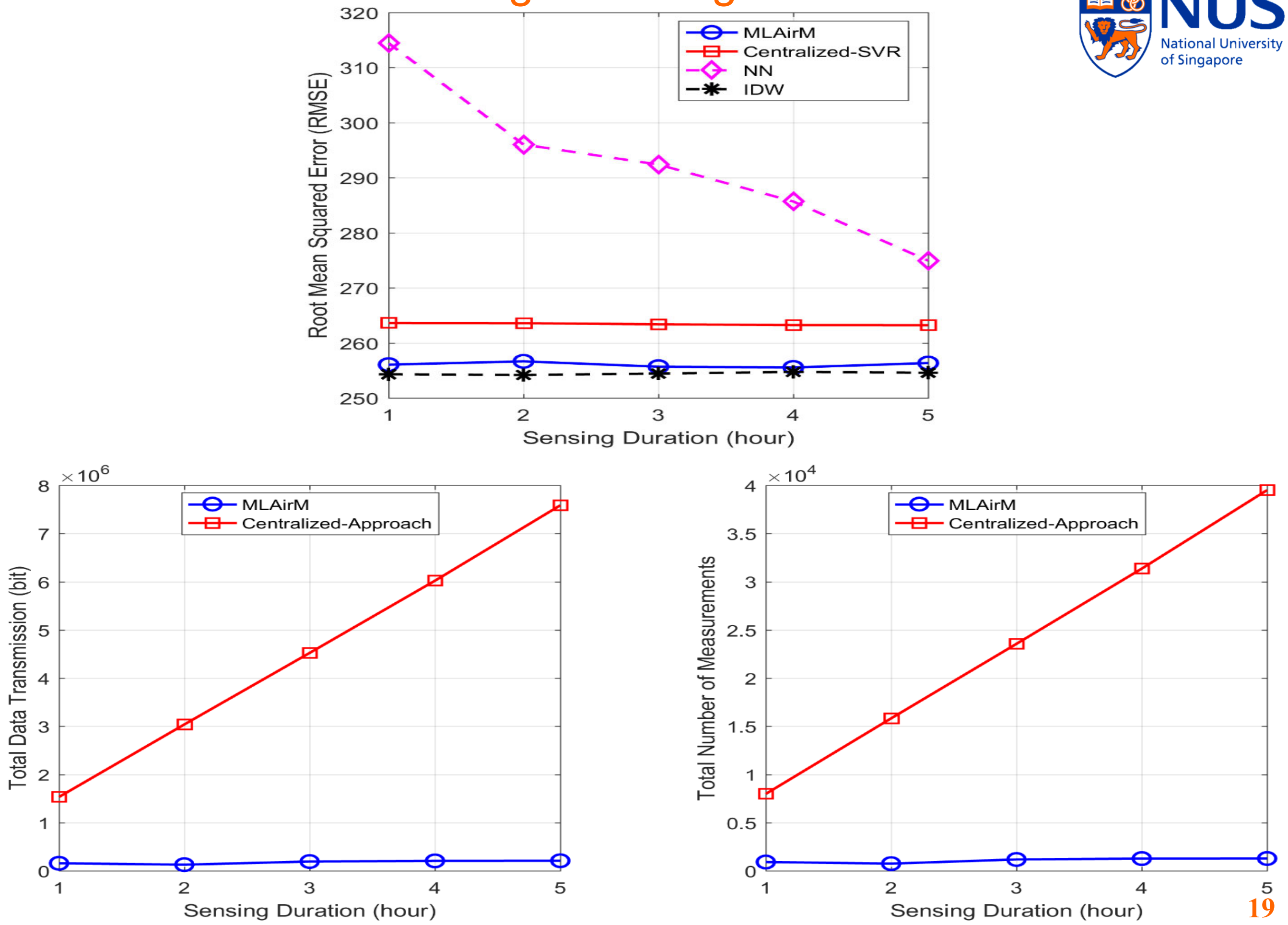
Performance Results: Change Number of Vehicles







Performance Results: Change Sensing Duration



Conclusions

- We propose a machine learning (ML)-based Air quality Monitoring (MLAirM) system using the vehicular sensor networks (VSNs).
- Each vehicle utilizes the support vector regression (SVR) algorithm to learn a local model of the air quality.
- We focused on the problem of optimally assigning the sensing locations to vehicles
- An optimization problem is formulated and a greedy algorithm is proposed to find the assignment solution.
- The simulations results based on realistic vehicular traces show that the proposed MLAirM system can achieve a similar accuracy with a significant reduction in communication and sensing costs compared to other approaches.

Thank You