# Environmental monitoring under uncertainty using smart vehicular ad hoc network

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**Abstract:** Due to the development of technology and increased human activities for sustained life, different environmental parameters are changing day by day. These environmental parameters are temperature, humidity, amount of Carbon monoxide, methane, smoke etc. Due to different technological and industrial activities, the values of all these parameters are increasing day by day. Increase in these parameters has an adverse effect on human beings. So environmental monitoring is essential at regular interval of time. Nowadays VANET is the emerging technology which provides both safety as well as non-safety applications. Networking through vehicles is called VANET. In this paper, by using different sensors and VANET different environmental parameters are monitored using fuzzy transformation function regularly. Based on the monitoring the values we can classify a particular region as low zone region, medium zone region, high or critical zone region.

**Keywords:** VANET, Environmental parameters, transformation function

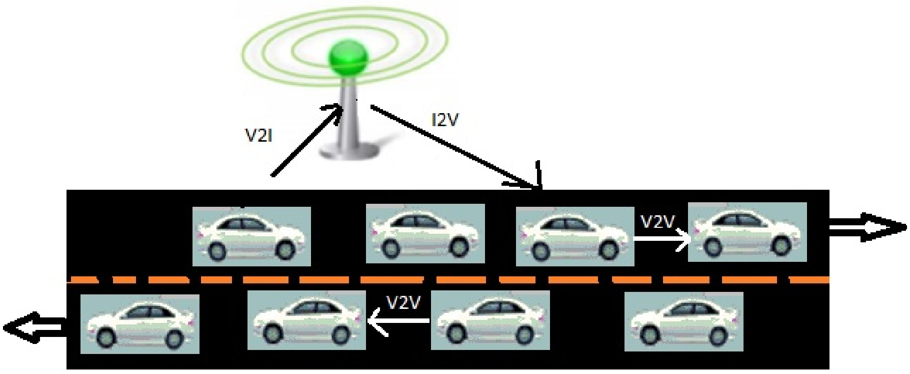
## 1 Introduction

In the recent years, the rate of development of technology is changing at a faster rate. Undoubtedly this results in the comfort of human life. But at the same time, this technological development and industrialization have the adverse effect on the environment. Various technological and industrial activities affect the ecological balance. Nowadays, technological development is affecting the environment severely. The value of different environmental parameters is increasing day by day. These environmental parameters are temperature, humidity, amount of carbon dioxide, amount of carbon monoxide, methane, smoke etc.

The increase in the different environmental parameters has the adverse effect on the human life. In the worldwide, the leading cause of death is the cardiovascular disease. The main reason behind this cardiovascular disease is the high temperature. The increase in humidity also affects the human health. Some health risk due to increase in humidity is dehydration, fatigue, muscle cramp, fainting, heat exhaustion, heat stroke etc. Increase in the level of $CO_2$ also raises the atmospheric temperature. Increase in $CO_2$ also affects the field of agriculture. Production of rice, the nutritional quality of vegetable decreases due to rising of $CO_2$ in the atmosphere. Carbon monoxide (CO) is a toxic gas. Increase in the level of CO also affects human health. Breathing CO can cause a headache, dizziness, nausea, vomiting etc. Exposure to high levels of CO can cause unconsciousness or death of a person, and exposure to moderate levels of CO also increases the risk of heart disease. Increase in methane can cause different health problems like suffocation, unconsciousness, dizziness, nausea, vomiting etc. The increase of smoke also affect health indifferent way like it may cause lung cancer, heart disease, bronchitis, persistent coughing, infertility etc. Looking at the different hazards of the increase in environmental parameters, it is important to monitor the environmental parameters regularly and necessary actions must be taken for a particular region for the increase in the value of these parameters in that region.

For the monitoring of environmental parameters, we can use a vehicular ad hoc network (VANET) and machine learning approach. VANET is used for the transmission of environmental parameters from one location to another and the machine learning approach is used for the smart computation of the environmental parameters.

VANET is the special case of MANET where the mobile nodes are the vehicles. The architecture of VANET consists of vehicles, Road Side Unit (RSU) [1]. Figure 1 shows the types of communication in VANET.




(Fig-1: Types of communication in VANET)

Communication in VANET is of two types. Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) or Infrastructure to Vehicle (I2V). Nowadays, the smart vehicular ad-hoc network is an important research area for all the government and private organization to give safety and security in emergency situations. Many companies provide connected car services (smart vehicular ad-hoc network) to the client for safety and security purposes [2] [3]. The smart vehicular ad-hoc network is a system consisting of the smart multi-functional sensor unit, GPS, storage unit, transmitter, receiver, computational power, and router [2]. The communication between vehicular networks is performed using dedicated short-range communication (DSRC) [4].

The major contribution of this paper is as follows.

(a) Transmission of environmental parameters from one region to the base station through VANET with a minimum end to end delay.

(b) Computation of environmental parameters using transformation function i.e. Gaussian fuzzy membership function by which the region can be classified as low zone region, medium zone region, and high zone region.

The remaining of the paper is organized as follows. Section 2 presents the motivation for this paper. Section 3 presents the proposed model for the classification of the region by computing the environmental parameters. Section 4 presents the simulation and result. Section 5 presents the experimental validation of the proposed algorithm. At last conclusion and future work is presented in section 6.

## 2. Motivation

Increase in the gaseous components of air like carbon dioxide, carbon monoxide, methane, etc. in the urban and rural area is due to pollution, industrial waste decomposition, fuel burning, forest firing, and enormous vehicle driving. Increase in these environmental parameters has a various hazardous effect on human health and life. Thus, continuous monitoring of environmental parameters is required for safety and criticality issues of the environment. The main focus of this work is to continuous monitoring of the environmental uncertainty data in the urban or rural area using a smart transport system. The uncertainty in the collected sensor data could cause the failure sensor system [5], which leads to human life-threatening events. The uncertainty in the sensor reading could emerge due to failure sensor module [6], an unexpected alteration in the environment, and interrupts of some unknown factors. So, the environment monitoring [7] requires an adaptive model to acquire the environmental changes with respect to time and robust in nature. After the monitoring, the location of critical zone information is passed to the control center called base station by smart transportation system in minimum time to take necessary action against SOS situations. This work is tested in a city environment with the sensor node, RSU unit, and a smart vehicular network.

Automated monitoring of environment is preferable because of the cause that it requires very few human interpretations to execute the model. So, it has a very demanding and stimulating task for researchers. In this work, we have collected the uncertainty sensor readings for further processing.

## 3 Proposed model

The method is implemented in two phases. In the first phase, the smart vehicle collects the environment parameters while moving in the road side unit and continuously sends to the RSU units. Then the data is processed in the RSU unit to determine the air quality. When the measured parameter is greater than the critical level threshold value, then the location information is transferred by the vehicle (the location information is determined by GPS unit). The critical zone information is sent to the control center in a minimum time by using RSU unit in multi-hop transmission.

The uncertainty environment data are handled by a Gaussian fuzzy membership function [8, 9]. The Gaussian function is also called a transformation function, which transfers a single data value into the different degree of belongingness with respect to threshold conditions. It transfers the one-dimensional data into multi-dimensional data, which are easily classified with respect to the different threshold conditions. For example, $x$ is a sensor reading belongs to either low, or medium, or high value. So, we require a transformation function to transfer the data into the degree of belongingness with respect to different classes such as belongingness of low, medium, or high class. The function is denoted in Equation (1).

$$f(sn_i) = d \times \exp\left(-\frac{(sn_i - \theta)^2}{2 \times \sigma^2}\right) \tag{1}$$

Here sensor readings $\{sn_1, sn_2, \ldots, sn_m\} \in sn_i$, d is the maximum value of the degree of membership, θ is the threshold for a different class of belongingness (θ is defined in equation (2)), and σ is the standard deviation of readings.

$$\theta = \begin{Bmatrix} \min(sn_i) & for\ low\ degree \\ mean\ (sn_i) & for\ average\ degree \\ \max(sn_i) & for\ high\ degree \end{Bmatrix} \tag{2}$$

The range of degree is varied from 0 to 1. So, the maximum value of membership d = 1. The data analysis process runs in two phases. In the training phase, we have collected some historical sensor data of the environmental parameters. The collected data are processed using the training algorithm and the minimum, average, and maximum threshold values are determined for further processing. Then dynamically sensor data are collected using a VANET network (these data are not used in the training phase). The dynamical sensor data are used in the testing phase for classification of the sensor data into different classes. According to the threshold setting, the data are classified into different zones (low zone, medium zone, high or critical zone). For critical zone, the location information is transferred by the VANET multi-hop communication in the minimum time to the control center for deciding the necessary action against the critical situation. Algorithm 1 describes the training and testing phase of data processing respectively.

```
1.  Input: Sensor readings;
2.  Output: To classify the sensor readings into lower zone, average zone, and higher
    or critical zone;
3.  Set θ1, θ2, and θ3 threshold value by using min, avg, and max value from training
    process respectively;
4.  Calculate standard deviation σ;
5.  Collect the sensor readings sni ← {sn1, sn2, …, snm};
6.  for each sensor reading i = 1 to m do
7.      Ylow (i) = 1 × ( exp (-((sni – θ1 )^2/(2 × σ^2))));
8.      Yavg (i) = 1 × ( exp (-((sni – θ2)^2/(2 × σ^2))));
9.      Yhigh (i) = 1 × ( exp (-((sni – θ3)^2/(2 × σ^2))));
10. end for
11. for i = 1 to m do
12.         if  Ylow (i) > Yavg (i) && Ylow (i) > Yhigh (i) then
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            Sensor reading belongs to lower zone region;
        else if Yavg (i) > Ylow (i) && Yavg (i) > Yhigh (i) then
            Sensor reading belongs to medium zone region;
        else if Yhigh (i) > Ylow (i)  && Yhigh (i) > Yavg (i) then
                  Sensor reading belongs to the critical zone region;
             else
                  Sensor reading belongs to unspecified zone;
            end if
end for
If sensor reading belongs to critical zone then
     Broadcast a message through VANET;
end if
```

(Algorithm-1: Training and testing phase data processing)

## 4 Simulation & Result

The performance of the proposed algorithm is evaluated by using MATLAB R2015a tool. Simulations are carried out in a machine which has the configuration of Core i7 processor, 6GB RAM, and Windows 10 platform. The performance of the algorithm is evaluated at the base station.

4.1 Results

Environmental parameters for the region are analyzed and based on the simulation the region is classified as a low zone, medium zone, and high zone or critical zone. Figure-2 shows the fuzzy transformation of CO sensor data, and temperature sensor data into the degree of belongingness with respect to different classification zone. In this figure, data is collected in a continuous manner.

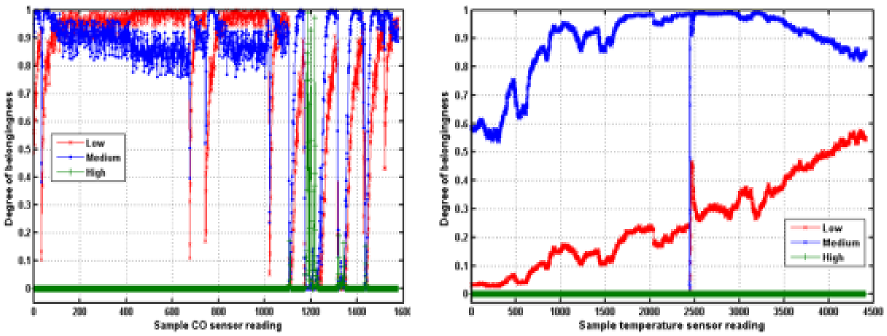


Figure-2

Figure-3 shows the fuzzy transformation of smoke sensor data, and humidity sensor data into the degree of belongingness with respect to different classification zone. In this figure, data is collected in a discrete manner. Figure-4 shows the fuzzy transformation of methane sensor data into the degree of belongingness with respect to different classification zone. In this figure, data is collected in a discrete manner.

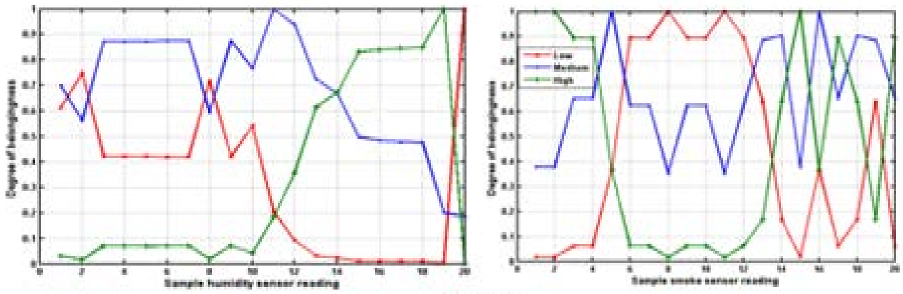


Figure-3

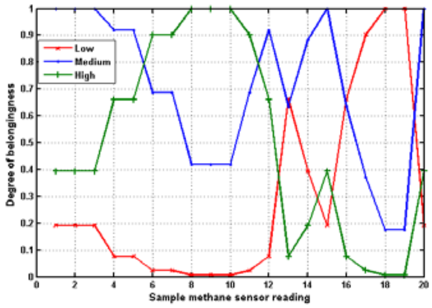


Figure-4

## 4 Experiment and Results

For the fuzzy transformation of different environmental parameters into degree of belongingness, an experiment has been conducted in outdoor Rourkela city environment. Figure-5 shows the experimental test set up for RSU unit and also the data collection from the RSU unit at the base station.


Figure-5 Experimental set up of RSU and base station in Rourkela city

Table 1 shows the values of the different parameters used for the setup of the experiment.

**Table-1** Experimental set up for environmental data transmission

| Parameter | Parameter Value |
|---|---|
| Transceiver module (dBm) | MRF24J40MD |
| Frequency (GHz) | 2.405-2.48 |
| Channel frequency (GHz) | 2.405 |
| Power of transmission (dBm) | 20 |
| IEEE standard | IEEE 802.15.4 |
| Sensitivity of receiver (dBm) | -104 |
| Data receiving threshold (dBm) | -85 |
| Data rate | 250 Kbps |
| Distance (m) | 20-200 |

Figure-6 shows the set up for RSU unit and different sensors used for the measurement of different environmental parameters.

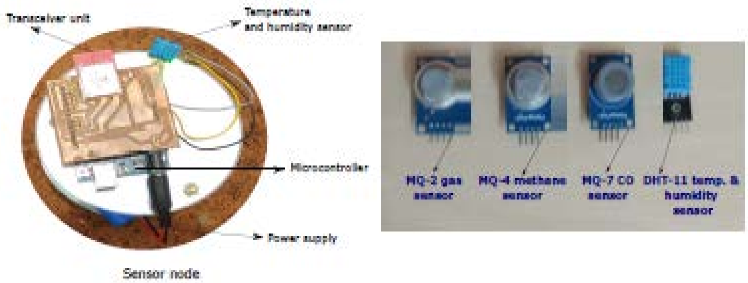


Figure-6 RSU unit set and different sensors

**Table-2** shows 10 temperature sensor readings with respect to different time instances.

| Sl. No. | Sensor Reading | Degree of belongingness w.r.t class low | Degree of belongingness w.r.t class medium | Degree of belongingness w.r.t class high |
|---|---|---|---|---|
| 1 | 25.00 | 1.0000 | 0.2932 | 0.0087 |
| 2 | 27.98 | 0.0087 | 0.3175 | 1.0000 |
| 3 | 26.15 | 0.4931 | 0.9313 | 0.1669 |
| 4 | 26.03 | 0.5671 | 0.8818 | 0.1310 |
| 5 | 25.74 | 0.7462 | 0.7254 | 0.0684 |
| 6 | 25.88 | 0.6610 | 0.8061 | 0.0946 |
| 7 | 27.75 | 0.0175 | 0.4425 | 0.9721 |
| 8 | 26.25 | 0.4337 | 0.9632 | 0.2019 |
| 9 | 27.42 | 0.0437 | 0.6454 | 0.8456 |
| 10 | 26.95 | 0.1310 | 0.9038 | 0.5671 |

**Table 3** shows the degree of belongingness of sensor readings with respect to different classes such as low, medium, and high using Gaussian fuzzy membership function.

| Sl. No. | Sensor Reading | Classification |
|---|---|---|
| 1 | 25.00 | Class Low |
| 2 | 27.98 | Class High |
| 3 | 26.15 | Class Medium |
| 4 | 26.03 | Class Medium |
| 5 | 25.74 | Class Low |
| 6 | 25.88 | Class Medium |
| 7 | 27.75 | Class High |
| 8 | 26.25 | Class Medium |
| 9 | 27.42 | Class High |
| 10 | 26.95 | Class Medium |

## 4 Conclusion & Future Scope

In this paper, using different sensors, environmental parameters like temperature, humidity, methane, Carbon monoxide, and smoke are measured and transmitted to the base station through RSU and vehicles. At the base station, using the proposed algorithm these parameters, the environmental region is classified as a low zone, average zone, and high or critical zone. From the results, it is observed that environmental monitoring is feasible using VANET and machine learning approach. We next plan to extend the work by performing experimental tests on a cloud platform.

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