Journal of Engineering Science and Technology
ICIST2022, Vol. 18, No. 1 (2023) 71 - 89

THE EFFECTIVENESS OF MULTI-SEN SOR SYSTEMS IN MONITORING POLLUTION LEVELS

ADE SILVIA HANDAYANI[1], NYAYU LATIFAH HUSNI[1,*], AHMAD TAQWA[1], WAHYU CAESARENDRA[2]

[1]Politeknik Negeri Sriwijaya, Indonesia & Engineering Electrical, Indonesia
2Universiti Brunei Darussalam & Diponegoro University, Brunei Darussalam
*Corresponding author: nyayu_latifah@polsri.ac.id

Abstract

A multi-sensor network technology is proposed in this study. This technology is applied at the semi-closed motorcycle parking area of Politeknik Negeri Sriwijaya. The sensor node is composed of a multi-sensor, and there are six characteristics of pollutant levels that are continuously measured. These parameters include Carbon Monoxide (CO), Carbon Dioxide (CO_2), HydroCarbon (HC), temperature, humidity, and particulates (PM10). The data can be monitored using a mobile phone. A Support Vector Machine (SVM) is supplied to the system to enhance the classification validity and accuracy. The proposed device gives 95.02% accuracy and only 4.98% classification error for node 1, while for node 2, it provides 99.3% accuracy and 0.05% error, and for node 3, it gives 95.03% accuracy and 4.97% error. The resulting device is efficient for economic sensor-based air quality monitoring.

Keywords: Air pollution, Indoor parking, Low-cost, Multi-sensor, Performance.

1. Introduction

Air pollution happens when the air quality becomes contaminated by dangerous chemicals such as toxic metals, particles, and gases. This issue can result in health concerns. Several factors caused the increase in air pollution, such as the development of the infrastructure, the smoke produced by the factory, and the gas exhausted by vehicles. [1-3]. The existence of air pollution can cause various diseases, including eye irritation, upper respiratory tract infection, sore throat, and even fatality [4, 5]. According to information provided by the World Health Organization (WHO), over 4.2 million individuals have lost their lives due to air pollution. In other words, it is possible to say that around 5% of the 55 million individuals who pass away yearly around the world do so as a direct result of air pollution. Specifically, there will be 1.5 billion individuals who die prematurely in the cities of Asia. As a result, one might get the following conclusion: the rates of death brought on by environmental contamination is significantly higher [6, 7].

Jakarta is one of the largest most populated cities in Indonesia. Therefore, it also becomes the most polluted city. It has high amounts of particulate matter and carbon monoxide in the air [8]. Most of these chemical substances are produced by vehicles that grow rapidly. A number of vehicles were continuously manufactured and increased nearly 10% each year. The Central Statistics Agency (BPS) recorded that the number of vehicles in Indonesia reached 136.32 million units in 2020. There are 115.29 million motorcycles, 15.8 million cars, 5.01 million trucks, and 233.42 thousand buses [9]. The increasing number of transportation modes will impact the rise of the air pollution caused by gases exhausted by vehicles. It is due to the increasing number of vehicles used that may result in the increasing emissions of air pollutants, such as carbon dioxide (CO_2), carbon monoxide (CO), particle matter (PM), nitrogen dioxide (NO_2), and volatile organic compounds (VOCs). Various studies have been conducted to develop scenarios for emission reduction [10]. Some policies are declared to decrease emissions. One of them is the recommendation of using the reduced fuels and low-emission vehicles. However, this policy implementation needs time, and it is not comparable with vehicle growth. The rate of vehicle growth is much higher than the consciousness of the community to keep the environment safe and sound.

Indonesia has developed a severe problem with indoor and outdoor air pollution in recent years. The quality of the air outside has a significant influence, in general, on indoor air quality. As a result, the quality of the indoor and outdoor air should receive increased attention [11]. The Environmental Protection Agency (EPA) reports that the pollutants found within buildings can be up to one hundred times higher than those found outdoors. The studies in the air provide additional evidence for this reality [12]. They have established the fact that indoor air is more hazardous than outdoor.

The health risks posed by poor indoor air quality are significant [13]. They become one of the many environmental hazards that are harmful to human beings [11, 14]. It is due to humans usually spending 90% of their time indoors. As the number of industries and vehicles increases in the urban areas, toxic gas emissions will increase the severe impact on the general human's health issues, such as coughing, wheezing, and asthma [15-17]. Poor air quality may contribute to acute health problems such as fatigue and nausea, chronic respiratory diseases, cardiovascular disease, and cancer [1, 4, 18].

Nowadays, the increasing health concerns related to indoor air pollution have become a serious topic of discussion for researchers all over the world. Most of them spared much time in analyzing the harmful pollutants, such as Carbon monoxide (CO), particulate matter (PM), volatile organic compounds (VOCs), aerosol, biological pollutants, that can be found in indoor environments [19]. Some of them focus on indoor pollution, such as in underground parking. As the number of cars increases, the number of underground parking spaces also increases. Moreover, currently, newly constructed commercial and residential districts are developed equipped with the underground parking that has small ventilated spaces [20]. However, the high traffic in these facilities impacts the quality of the indoor air. In indoor parking, the air pollution produced by vehicles not only has long-term and negative consequences for human health but also has a bad effect on the environment [21].

Recently, the application of technologies such as the Internet of Things (IoT), machine learning, and big data in real-time indoor air quality monitoring has also attracted researchers' interest. The Internet of Things has made it possible to monitor and control the air quality inside buildings with relative ease. There are currently some Internet of Things-based indoor air quality monitoring devices available on the market. These systems include open-source software for the processing and transmission of data. [22, 23]. Previous studies based on wireless sensor networks (WSN) have been applied in indoor air pollution monitoring applications [24-26].

WSN consists mainly of sensor nodes with the critical function of collecting information from sensors. Most WSNs consist of a decentralized sensor network communicating with an external cloud. Some sensor network data collection has also been done while optimizing cloud computing systems [27]. Currently, this system also incorporates artificial intelligence approaches to optimize the detection of pollutants. The researchers also examined a different technology, a Multi-Sensor Network (MSN) design [28-30] which integrates many sensors with a Wireless Sensor Network (WSN). The information gathered by these sensors is related to a central monitoring station using an intelligent device. This central monitoring station then uses this information to manage the dispersed resources autonomously and to optimize processes in real-time [31-33]. This system can deliver object data that is automatically detected by the sensors.

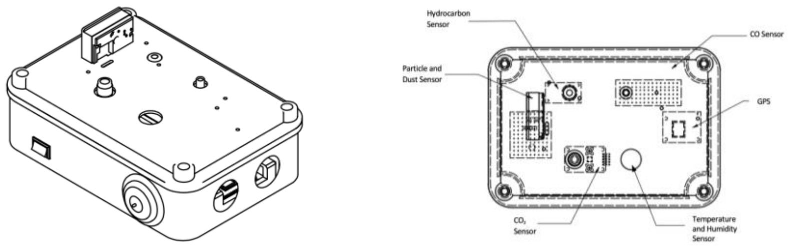
Recently, scientists who study the environment have shown a growing interest in developing low-cost sensors that can detect air pollution with high temporal and spatial resolution. However, even though the sensors' accuracy, precision, sensitivity, and specificity are all increased, these sensors have a lower price tag. [34]. They can overcome some limitations of traditional techniques and therefore, it becomes a priority in air quality monitoring. It is due to not only that they are inexpensive but also they have superiority, such as compact size, high temporal resolution, portability, and low power consumption [13, 35, 36].

In this study, the low cost Multi Sensor Network applied to air quality monitoring is investigated. The contribution of this paper is an automatic air monitoring device that can be applied in Indoor Parking Area. This research is a Real Time Operation System (RTOS), accurate, low-resource, portable, reliable, and at a low price. In addition, it is connected to an IoT application-based network. In this study, a SVM is used to determine the level of the air pollution. The SVM classifies the air pollution based on the data inputted to the Raspberry, such as the values of CO, CO_2, HC, dust particulate, humidity, and temperature. The SVM will process the data into 3 main steps, such as classifying the normal and abnormal, it is then continued to the moderate and unmoderated, and at last to classify the air pollution whether it is dangerous or safe. The output of the systems can be monitored in smartphones.

2.Materials and Methods

Multi-Sensor Network (MSN) has a task to connect many sensors of nodes into a single device. In this study, the MSN is built by 3 wireless air pollution nodes as presented in Fig. 1. Each node (as shown in Fig. 2) is composed of some electronic components that are arranged in such a way in an electrical box. Six important air quality sensors, such as DHT11, TGS2442, MG811, TGS2611, SharpGP2Y1010, and Neo-6M, are placed at the cover of the electrical box. Each sensor has a different function in detecting the air quality.

Fig. 1. Node label of sensor network device.



(a) Single node **(b) The top side of the device**

Fig. 2. The sketch of a monitoring device.

The specification of the sensors used in this research is presented in Table 1. The functions of the sensors in this research can be explained as follows: 1. DHT11 has a function to detect the temperature and humidity; 2. TGS2442 has a function to detect carbon monoxide (CO), 3. MG811 has a function to detect carbon dioxide (CO_2), 4. TGS2611 has a function to detect hydrocarbons (HC), 5. SharpGP2Y1010 has a function to detect the dust particulate, and 6. Neo-6M has a function as the GPS to detect the location of the monitored area. The connection of the electrical components is shown in Fig. 3. If Fig. 3 indicates the connection of node 1, then, the data from TGS2442, MG811, TGS2611, and Sharp GP2Y1010 will be converted into digital value by ADC1115 converter.

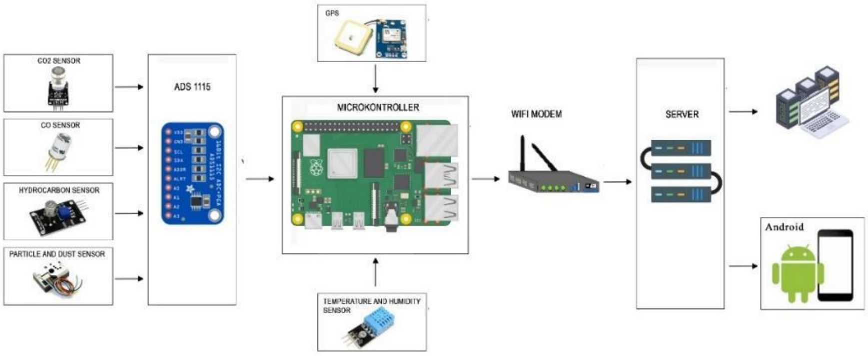


Fig. 3. Component connection of single node of the MSN.

Table 1. Specifications of the gas sensors used.

Parameter	Sensor type	Range	Accuracy	Time response
CO	TGS2442	30 ~ 1000 ppm	+/- 1	<= 33
CO_2	MG811	0~10,000ppm	0.04% to 1%	< 60s
HC	TGS2611	500 ~ 10,000 ppm	± 0.4°C and ± 3% RH	20-40 s
Dust	Sharp GP2Y1010	0 to 600 µg/m^3	±30%	1 s
Temperature and Humidity	DHT11	0-50 ^{0}C 20-90 %RH	+/- 2 ^{0}C +/- 5 % RH	1/e (63%) 25 ^{0}C m/s Air
Location	Neo-6M	0.25 Hz to 1 kHz	2.5 m	27s

The data are then inputted to the microcontroller. Apart from having the data from ADS1115, the microcontroller also obtains data from DHT11 and Neo-6M. All these sensors' data will be processed in the microcontroller. Adhao and Pawa [37] used a variety of sensors, including temperature, humidity, and water sensors to monitor soil quality, has found success using the SVM classifier algorithm written in Python code on the Raspberry Pi. The SVM that has a task to determine the pollution level of the air will also do its classification in this microcontroller. The data is then sent to the server through the help of Wi-Fi connection. In this research, the server will not only receive the data from one node, but also from the other node, namely node 2 and node 3. Thus, the same procedure of the node 1 that has been explained above, will also be processed by node 2 and node 3.

In this research, the microprocessor used is Raspbery Pi. Although the AT-Mega Microcontroller has been widely used to control real-time data collection, the Raspberry Pi is more robustly applied in MSN. The use of the ADS1115 converter is essential in this research due to Raspberry Pi can only read the output value digitally.

For communication to the server, the Raspberry Pi is connected to a Wi-Fi network. Raspberry Pi acts as a gateway that serves as an intermediary to forward data transmission before it enters the database server. The gateway can also be used as a place to store data logs. The use of Raspberry Pi can enhance the network capabilities. As an internet service provider, the Wi-Fi network in this research is established using a Wi-Fi modem. All the data that is entered to the database will be set into a determined storage. As the final output of the proposed system, the air quality data will be displayed, and the emergency air quality notifications will be sent when the monitoring device detects a danger. The air quality monitored in this research is divided into three categories: normal, moderate, and hazardous.

The wireless sensor network (WSN) technology that is used in this MSN research is an Ad Hoc Network. Due to the sensor network consuming a lot of energy when transmitting data in multiple hops, therefore, this research utilized an Internet of Things (IoT). It is intended to optimize the energy consumption and to increase the efficiency of one-hop communication capabilities. Nowadays, IoT monitoring system based on an android application has become the most efficient approach to be used, therefore, this study also uses android to be connected to the IoT system. This connection will establish good communication so that the air quality monitoring system can be conducted in further locations at any time and from any places. Another superiority of this system is it requires less maintenance, it needs low cost, and consumes less power. This device uses conventional IoT node-to-node communication technology.

To get valid experimental data, a reference value of the air quality is needed. In this study, the reference value is shown in Table 2 [38]. The final output obtained in this research was in the form of air pollution values. All obtained data was used to determine the success rate of system data accuracy. In addition, all of the data from the sensors was also used to determine the level of pollution, whether it is normal, moderate, or hazardous. The experimental testing was conducted in the state polytechnic of Sriwijaya parking area as presented in Fig. 4. It is a two-floor building, and it is a semi-closed parking area. The node was spread in 3 different places, namely, 1. In the left side (Fig. 4(a)), 2. In the middle (Fig. 4(b)) of the second floor parking area, and 3. On the first floor of the parking area Fig. 4(c)). The location of the nodes is shown using the yellow circle in each figure.

Table 2. Air pollution parameter.

Air pollution parameter	**Air quality**		
	Normal	**Moderate**	**Hazardous**
CO (ppm)	200-400	400-600	800-1600
CO_2 (ppm)	350-550	600-2500	2500-5000
HC (ppm)	0-5000	5000-9000	9000-10000
Dust (µg/m^3)	0-50	51-100	301-400
Temperature (^{o} C)	20-30	30-40	40-50

(a) node 1 **(b) node 2** **€ node 3**

Fig. 4. Nodes position in the parking area: (a) in the left; (b) in the middle of the 2nd floor; and (c) on the 1st floor.

Support vector machine

There are many methods available for estimating the amounts of pollutants that can be used for creating predictions or predictions regarding the quality of the air. Some of the methods used include fuzzy logic [39], artificial neural networks [40], hidden 77nalys models [41], sensor vector machine [42]. In this research for determining the air quality level in order to show its status, an SVM technique is used. The flowchart of the SVM method is presented in Fig. 5. At the beginning, the sensors in the device will detect the air. If the sensor cannot read the data, the step will go back to the initialization. However, when it detects the surrounding air well, the data will be inputted to the SVM classifier to be processed more. At the end, the data processed will be outputted as the classified air quality.

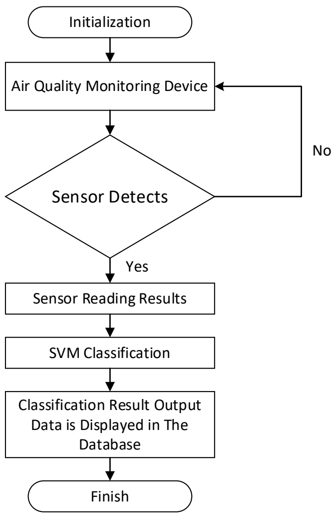


Fig. 5. A network of node sensor device.

The SVM can be generated using some steps that are shown in Fig. 6. Machine learning works the same as humans. This learning process uses data that is called training data. This training data is in the form of a datasheet that contains parameters with a range of reading values of each sensor that are used for detecting a particle in the air. The three classification parameters used in this study are Normal (0.0), Moderate (1.0), and Hazardous (2.0). In addition, the range of values in the training data uses data from previous studies. This is to achieve a certain performance, so that an efficient model can be produced.

Furthermore, from the training data, the computer will do a learning process (trained) to produce a model. This learning process uses a machine learning algorithm, namely the SVM algorithm. Thus, in this research, the training data will be entered into the SVM algorithm for the learning process. This learning process requires several iterations so that it can produce a model. This model will be used many times to predict air quality during testing. Therefore, the resulting model contains information that is used as a reference to solve an input-output process problem so that it can make predictions in the form of classification results. To ensure the efficiency of the model formed, a model suitability test was carried out. This aims to see how much performance is generated by the model in recognizing patterns in data. The training data screenshot can be seen in Fig. 7.

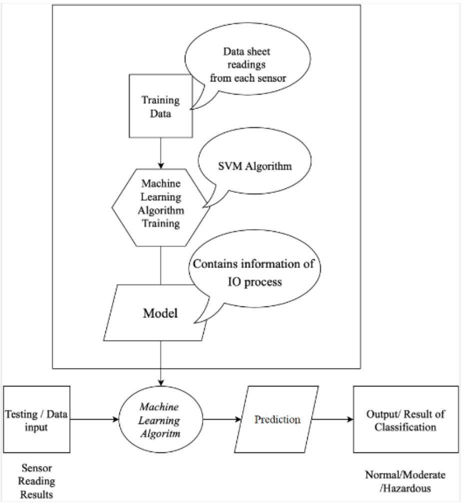


Fig. 6. Machine learning process.

Sensor TGS-2442	Sensor MG-811	Sensor TGS-2611	Sensor DHT-11
21	350	1375.5	22.55
95	433.5	1825	27.2
46	502.5	2527.5	20.1
56	525.5	700	23.67
40	452	1145.5	27.14
101	431.5	1565	21.23
103	453.5	2300.5	24.92
39	542	2680	26.84
98	355	3329.5	21.26
24	353.5	3734	29.75
111	353	4452.5	24.98
86	450	4115	26.89
115	433	5000	22.44
51	435	1000.5	28.35
31	355.5	1425	20.7
117	351.5	2812.5	24.96
64	480	2778	27.17
109	376	3310.5	28.32
113	400	3686	23.7
94	477	4298.5	28.39
30	377	4450	25.57
82	482	4272.5	26.87
59	478	2500	23.63
91	528.5	2978.5	29.77

(a)

571	840	5395.6	36.98
497	965.5	5843.1	31.42
433	1425	6553.9	35.79
527	1538.5	7744.5	30.2
581	1800	8294.4	38.85
469	2295.5	8709.2	34.29
438	2425	4147.5	32.31
546	850.5	5286.5	33.64
585	950	6401.6	37.51
526	600.5	6778.4	39.3
417	760	7482.1	37.56
540	880.5	8153.6	33.68
589	1300	8959.4	30.17
547	1440.5	4418.6	36.95
454	1542.6	5572.1	35.77
434	1700	6122.4	39.11
542	2008.9	7261.8	32.36
509	2375.2	8498.6	30.14
499	2500.4	8700.1	38.82
522	730	8944.9	34.25
465	1350.8	5361.9	31.43
416	1445	4632.1	39.19
432	1652.5	6218.4	33.61
460	1841	6641.8	35.74
548	2152.5	7372.7	37.59

(b)

1481	3100.6	9078	41.59
1371	3250.7	9280.1	45.27
1140	2900.5	9720	43.8
956	3840	9005.2	46.33
990	4005.5	9170	48.7
952	4340	9595.3	40.38
1260	4850	9790	44.92
1489	3100.9	9200.4	47.41
804	3200.7	9875	40.36
886	2750.3	9520.5	49.13
1540	3820	9075	42.65
1262	2500	9330.6	45.21
1150	3250	9955	43.85
889	4250	9472.7	48.73
1580	5000	9625	40.33
847	2520	9474.8	49.11
1485	3350	9775	46.31
954	4000	9660.9	48.76
958	3950	9925	41.54
1130	4310	9002	45.22
1377	4750	9390.1	42.68
1373	2500.5	9801	47.47
803	2510	9500.2	43.89
881	3110	9076	46.37
842	2890.2	9725.3	44.96

€

Fig. 7. Screenshot of training data:
(a) Normal, (b) Moderate, and (c) Hazardous.

3. Results and Discussion

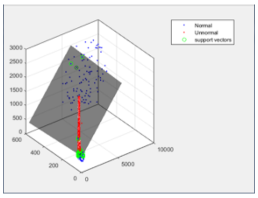
This study aims to determine the accuracy value, precision, and recall of each node that is a part of a multi-sensor network used to monitor air quality. At each node, the air quality characteristics are measured from a multitude of sensors positioned in a variety of different positions. Knowing which node has good accuracy values, a high precision level, and the best recall value and the data provides this information. The results of this research can be utilized in estimating the level of air pollution present in a variety of locations thanks to the information provided by these findings.

3.1. Support vector machine (SVM) simulation

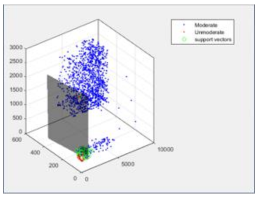
To analyze the performance of the proposed SVM in determining the level of the air pollution, an experimental simulation was conducted. The result is shown in Fig. 8. The simulation of node 1, node 2, and node 3, is shown in Figs. 8(a)-(c), Figs. 8(d)-(f), and Figs. 8(g)-(i). Basically, the SVM can only distinguish between two classes, namely +1 and -1. According to Figs. 8(a), (d) and (g), it can be seen that classes are separated by a gray plane, in order to classify the class into the normal and the abnormal one. Figs. 8(a), (d), and (g), show the normal class of the air pollution. For the SVM to function, it must first determine which classes are categorized as normal (+1) and which are categorized as abnormal (-1). If the data distribution is included in the normal area, it indicates that the sensor values in that area are considered normal. This is the case if the normal area is part of the distribution. But if the data distribution is in an abnormal area, then the system will move on to the next step in the process. At this point, the system should reconsider whether or not the sensor data in that area are categorized as moderate. Figures. 8(b), (e), and (h) show the data distribution results in the moderate class for nodes 1, 2, and 3, respectively.

It is plain to observe that the distribution of the data falls somewhere in the middle of the two extremes. The moderate class occupies the area of the right top face of the SVM cube. The green dots represent this class, most of which are located in this area. It indicates that the values measured by the sensors in that area are considered to be moderate. However, suppose the data distribution is included as an unmoderated one. In that case, the system will recheck whether the area's sensor readings are classed as hazardous or safe. This will happen only if the data distribution is included as an unmoderated one. Figure€(c), (f), and (g) illustrate the categorization of potentially hazardous forms of air pollution (i). It is clear from these figures that the SV' cube's left top face is occupied by the vast majority of the blue dots that denote the potentially harmful one.

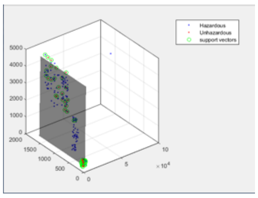
NODE 1



(a) Normal

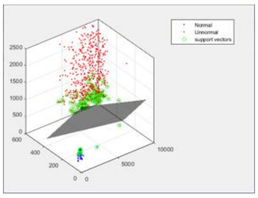


(b) Moder€

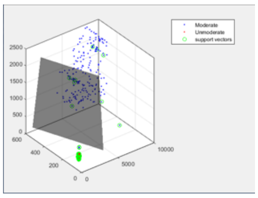


(c) Dangerous

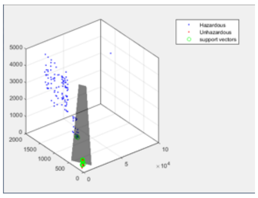
NODE 2



(d) €mal

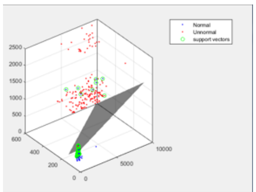


(e) Moderate

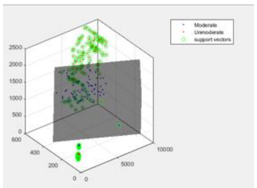


(f) Dangerous

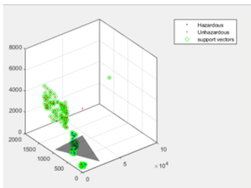
NODE 3



(g) Normal



(h) Moderate



(i) Dangerous

Fig. 8. SVM simulation.

3.2. Performance mea80nalyses80ory multisensor networks

The real experiments of the MSN monitoring in this research were conducted in 3 locations as shown in Fig. 4 in section 2. Each node that was deployed at one of State Polytechnic of Sriwijaya' parking areas, recorded the data of CO, CO_2, HC, PM10, dust particulate, temperature, humidity, and the location of the experiments. The sampled data of the real experiment is displayed in Figs. 9-11. This sampled data was obtained on July 13, 14, 15, and 17, 2020 (Table 3-6). In this step, only 4 days sampling data are presented to test the performance of the proposed monitoring device and it works effectively.

(a) **(b)**

(c) **(d)**

Fig. 9. Data of node 1.

The data of node 1 was collected in 4 days (Monday, Tuesday, Wednesday and Friday). The experiment was conducted at 07:30-20:30. Figure 9(a) shows the average air pollution 15 ppm of CO, 457 ppm of CO_2, 426 ppm of HC, and 27g/m^3 of dust. The observed air temperature in this area was-between 28 - 33 °C, with a humidity level of 58 to 70%. Temperatures have risen, and there has been a marked increase in CO_2 levels. This situation has arisen directly from the high temperatures and bright sunshine. Furthermore, the rise in CO_2 that took place at 01.30 was caused by the fact that it was the break period during which a large number of cars were operating. This condition ultimately caused the air pollution in the area. The measurement results show an increasing trend and are above the tolerance level for health.

Figure 9(b) illustrates the parameter average air pollution of 18 ppm of CO, 378 ppm of CO_2, 344 ppm of HC, and 23 g/m^3 of dust. The average temperature detected was 31^{o}C, with a relative humidity of 70%. Figs. 9(a)-(d) show that the CO (carbon dioxide) level in the monitored area was relatively stable between 15 and 26 ppm. Due to a lack of air circulation in the indoor parking space, the highest

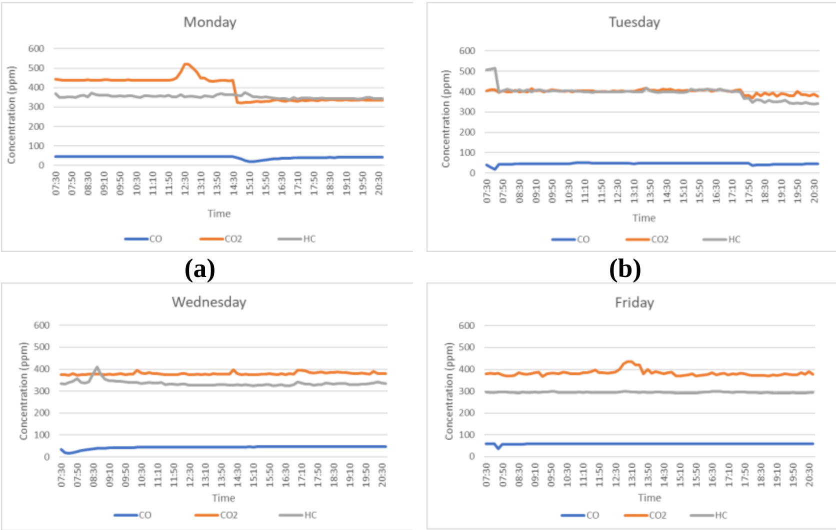
CO detected value is higher than the threshold value. The greatest concentrations of carbon dioxide for a day result in the highest carbon dioxide levels. The HC concentration observed is over the prescribed threshold, with a value of 300ppm to 550ppm. Meanwhile, the CO_2 level is below 1,000 parts per million, considered safe. The daily average concentration of dust particles in this area varies between 20 and 70 ug/m^3, which falls into the mild to moderate category.

The measurements show that ai€ pollution is moderate when the weather is sunny because the area is close to the source of pollutants from vehicle emissions as presenting Fig. 9(c). The average level of air pollution that exceeds the limits of good air quality is only visible in Carbon Monoxide (CO); this is because the parking building is a place for motorized vehicles to pass, which is the main source of CO.

The results of increased CO measurements than the previous day are shown in Fig. 9(d), with fluctuations in CO parameter values starting at 10.50-15.00. The morning peak session on Friday is later than on other days. The results of an experiment conducted at multi-sensor node 1 indicate moderate air quality conditions at that location. This is because the parking lot area serve' as automobiles' primary entry and exit points. The poor air quality directly results from the high volume of vehicular traffic that frequently passes through the area. At this stage, the precision and the margin of error of the system's reading of the air conditioner are determined and comp'ted. The device's accuracy was determined to be 95.02% based on the testing data, with a categorization error of 4.98%. The sensor readings incorrectly classified the air concentration into the incorrect class, leading to classification mistakes.

Figures 10(a)-(d) show the input value of the multi-sensor node 2, which can be found in graph (d). During the experiment, from 07:30 to 20:30, the average values detected for CO were 42 ppm, the average value of CO_2 390 ppm, the average value for HC 353 ppm, and the average value for dust 11 g/m^3. The temperature is currently at 31 degrees Celsius, and the humidity level is 68%. The results of the sensor detection were classified as normal classification, as illustrated in Fig. 10 (d). During the test with the device between 11.45 and 14.30, the detection findings showed that the CO concentrations were 57 ppm, CO_2 was 437 ppm, HC was 375 ppm, and dust was 23 g/m^3. Figure 10 presents the temperature, 32 degrees Celsius, and the humidity level, which was 68%. (b). The detection results from the second multi-sensor node have been assigned a moderate categorization. An increase in CO_2·causes that day's activities, and that break time allows many cars to pass by. According to the results of the tests, the device accuracy is 99.33%, with a minimal categorization error of 0.05%.

The input value of the multi-sensor node three is shown in Figs. 11(a)-(d), and the temperature and humidity readings are, on average, between 27 and 35 degrees Celsius and between 55 and 78 percent. Experiments were conducted between 07:30 and 20:30, the same as with the multi-sensor nodes 1 and 2. In Figs 11(a), the detected parameter values show that the concentration of CO was 65 ppm, the concentration of CO_2 was 400 ppm, the concentration of HC was 477 ppm, and the concentration of dust was 27 g/m^3. In this condition, the results of the detection of the sensor are normal classification.



(a) (b)

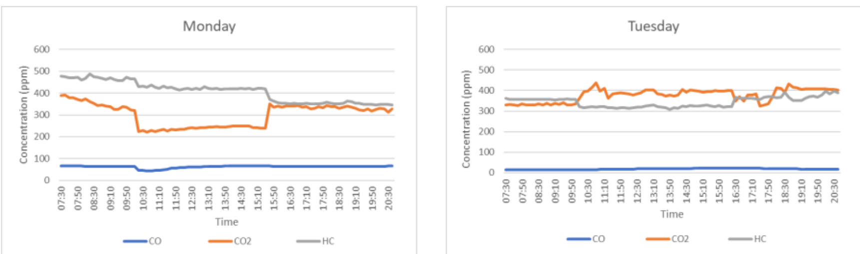
(c) (d)

Fig. 10. Data of node 2.

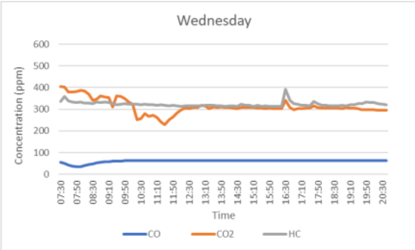
In Fig. 11(b), the detected parameter values include 65 ppm for CO, 315 ppm for CO_2, 380 ppm for HC, 24 g/m^3 for the dust, a temperature of 27 degrees Celsius, and a humidity level of 66%. In addition, the dust has a den-ity of 24 g/m^3 - the results of the sensor detection into the usual classification category. Even though the parking lot has a rush hour and a rest period between 11.30 and 14.30, the air quality is not abnormal in that area. The fact that there are so few activities in the area is responsible for the relatively high level of clean air in this location.

The results of the experiments conducted between 11.30 and 2.00 pm and displayed in Fig. 11(d) demonstrate that the measured values of the air quality parameters are as follows: CO at 48 ppm, CO_2 at 350 ppm, HC at 375 ppm, dust at 25 g/m^3, and a temperature of 31 degrees Celsius with a humidity level of 72%. The category is considered to be normal. The results are the same as the ones obtained in the earlier experiment. Because there aren't many things to do in this area, the air quality is goo', and there isn't much pollution. At this point, the device accuracy is 95.03%, whereas the categorization error is 4.97%.

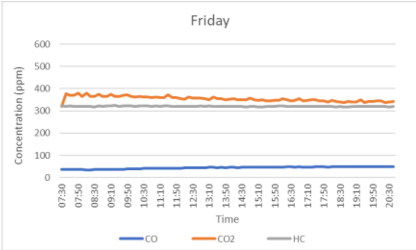
The average value that data measuring read from node 1, node 2, and node three are displayed in Table 3-6. The average value that the data measuring read from node 1, node 2, and node three are shown in Table 3-6. The moderate status is stated by each node.



(a) (b)



(c)



(d)

Fig. 11. Data of node 3.

Table 3. Monitoring on July 13, 2020, Monday.

Parameter	NODE 1	NODE 2	NODE 3
CO (ppm)	30	45	62
CO_2 (ppm)	525	445	327
HC (ppm)	403	361	429
Dust (μg/m^3)	40	12	21
Temperature (^{o} C)	33	33	34
Humidity (%)	75	71	79
Air Pollution Classification	**Moderate**	**Moderate**	**Moderate**

Table 4. Monitoring on July 14, 2020.

Parameter	NODE 1	NODE 2	NODE 3
CO (ppm)	34	45	58
CO_2 (ppm)	437	403	533
HC (ppm)	427	409	418
Dust (μg/m^3)	44	27	24
Temperature (^{o} C)	29	28	27
Humidity (%)	80	82	81
Air Pollution Classification	**Normal**	**Moderate**	**Moderate**

Table 4-6 displays the average value read from node 1, node 2, and node 3 with their respective statuses. This node has been positioned in a different area. Table 4, the measurements were taken on July 14, 2020, and Table 5, on July 15, 2020. The results of the measurements performed on Friday, July 17, 2020, are also included in Table 6.

Table 5. Monitoring on July 15, 2020.

Parameter	NODE 1	NODE 2	NODE 3
CO (ppm)	33	43	58
CO_2 (ppm)	445	394	405
HC (ppm)	460	340	360
Dust (μg/m^3)	44	17	23
Temperature (^{o} C)	31	31	34
Humidity (%)	74	72	69
Air Pollution Classification	**Moderate**	**Normal**	**Normal**

Table 6. Monitoring on July 17, 2020.

Parameter	NODE 1	NODE 2	NODE 3
CO (ppm)	36	58	50
CO_2 (ppm)	424	379	365
HC (ppm)	455	295	330
Dust (μg/m^3)	23	23	23
Temperature (^{o} C)	33	33	34
Humidity (%)	63	58	59
Air Pollution Classification	**Moderate**	**Moderate**	**Normal**

The data can be found easily using the mobile phone. Some sampling data that is displayed in android can be found in Fig. 12. The data was taken on July 21, 2020. In Fig. 12(a), the pollution shows that it is dangerous (it is indicated by the warning red circle that shows (hazardous situation). All of the sensors' data and the location can be monitored from the android that is shown in Fig. 12. The user can know the air in the determined area and the value of each gas, such as: CO, CO_2, HC, particulate dust. It also displays the value of humidity and temperature. In addition, it also shows the lo-cation of the nodes. Figures 12(b) and (c) show the value and the condition of the air of node 2 and node 3. The mobile phone can also display the graphical changes of the detected air pollution. The sample of the monitoring can be seen in Fig. 13. It only displays the data of node 1 that is obtained on July 21, 2020, at 9.45 until 10.25 a.m. According to Fig. 13, it can be seen that the mobile phone could monitor the air condition successfully.

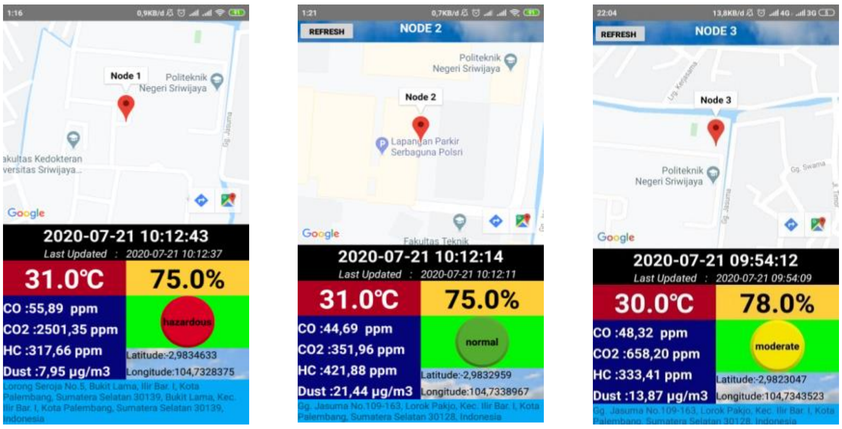


Fig. 12. The monitoring display on mobile phone: (a) Node 1; (b) Node 2; and (c) Node 3.

Figure 12 shows this device is a real-time operating system (RTOS). It is an operating system (OS) designed to service real-time application requests. It must process data as it arrives, typically without buffering delays. The results of device measurements can be viewed using an Android smartphone. It will display the measured data acquired from the multi-sensor equipment.

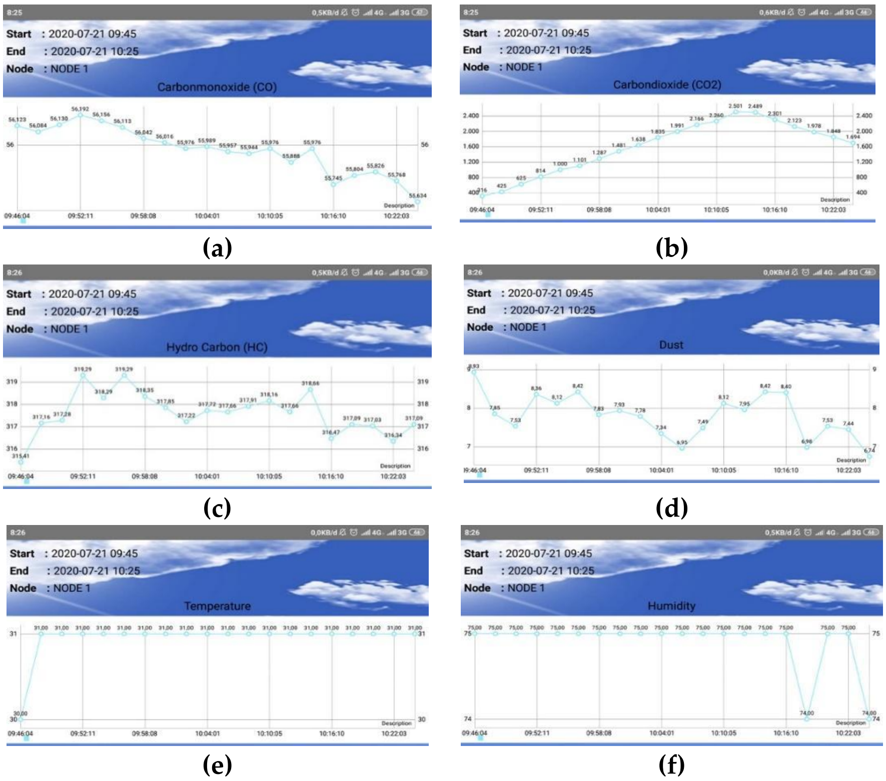


Fig. 13. The graphical result of the air monitoring of node on July 21, 2020, at 9.45 until 10.25 a.m. (a) CO; (b) CO_2; (c)€; (d) Dust; (e) Temperature; and (f) Humidity.

3.3. Comparative node multi-sensor of a location result

The accurate location may be determined with absolute accuracy [43] due to the precise range measurement. Therefore, it is essential to understand the internode distance accurately. In Table 7, the error in the position estimation for all unknown nodes spans from 0.007 m up to 6,205 m. When the node is positioned closer to the area's center, the error in estimating the location's estimation is significantly reduced. As a result of the experiment, the best position that the device acquired demonstrates that the anchor node density in the center of the site is considerably more significant than the density found along the place's perimeter.

Table 7. The location of the nodes.

Node	The estimated coordinate	The actual coordinate
	Latitude, Longitude	Latitude, Longitude
1	-2.99, 104.90	-2.983316667, 104.7328375
2	-3.00, 104.99	-2.983295934, 104.7338968
3	-2.99, 104.77	-2.982304732, 104.73435“4

In thi” study, "precision" refers to the degree of precision used to characterize the performance of the vast majority of measurements. According to the reference [44], when we talk about non dimensional precision estimates, we're talking about assessments that are based on relative disparities in data, whic' is something that's used a lot in the subject of air quality. On the other hand, if the observed concentrations are at most five to ten times the threshold for 'detection. They don't accurately characterize the data.

This research uses a method using multiple air monitoring instruments (by comparing a single parameter) simultaneously and in the same place. The Recall is the ratio of correctly identified air quality to real air quality detected, and using this performance metric [45], allows us to compare competing systems effectively. Specifically, Recall is defined as the ratio of correctly detected air quality to actual air quality "etected. The term ""alse positive rate" refers to the proportion of improperly detected air quality about the total number of erroneous air quality detections (FPR).

Table 8 is a recapitulation of the experimental findings of our approach. It shows that our system has achieved Recall = 96% and FPR = 4% for node 1, while node two and node 3 give 98.785 recall with 1.22% FRT and Recall = 99% with FPR = 1%, respectively.

Table 8. The prediction metric.

Node	Recall	False Positive Rate (FRT)
1	96 %	4 %
2	98.78 %	1.22 %
3	99 %	1 %

4. Conclusions

This work analyzes and discusses the concept of a real-time multi-sensor network that monitors indoor parking places. The primary objective is to develop a device in the form of a sensor node that is capable of real-time monitoring of Carbon Monoxide (CO), Carbon Dioxide (CO_2), HydroCarbon (HC), temperature, and humidity, in addition to the concentration level of particulate matter in the air (PM10). Using an application that is based on Android, one can monitor the outcomes of the measurements. Based on the results of the measures, there is a rise in CO_2 during breaks due to the vast number of vehicle activities that enhance pollution levels. The testing results show that the device has an accuracy of 99.33%, with a minimal error rate of categorization of 0.05%. In areas with good air quality and low pollution'levels, the device's accuracy is 95.03%, and its categorization error is 4.97%.

References

1. Sydbom, A.; Blomberg, A.; Parnia, S.; Stenfors, N.; Sandström, T.; and Dahlén, S.E. (2001). Health effects of diesel exhaust emissions. *European Respiration Journal*, 17(4), 733-746.
2. Thompson, J.E. (2016). Crowd-sourced air quality studies: A review of the literature & portable sensors. *Trends Environmental Analytical Chemistry*, 11, 23-34.
3. Hasunuma, H.; Ishimaru, Y.; Yoda, Y.; and Shima, M. (2014). Decline of ambient air pollution levels due to measures to control automobile emissions

and effects on the prevalence of respiratory and allergic disorders among children in Japan. *Environmental Research*, 131, 111-118.

4. Dehbi, H.M.; Blangiardo, M.; Gulliver, J.; Fecht, D.; De Hoogh, K.; Alkanaani, Z., … and Hansell, A.L. (2017). Air pollution and cardiovascular mortality with over 25 years follow-up: A combined analysis of two British cohorts. *Environment international*, 99(2), 275-281.
5. Yu, M.; Zhu, Y.; Lin, C.J.; Wang, S.; Xing, J., Jang, C.; … and Yu, L. (2019). Effects of air pollution control measures on air quality improvement in Guangzhou, China. *Journal of environmental management*, 244, 127-137.
6. Penney, D.; Benignus, V.; Kephalopoulos, S.; Kotzias, D.; Kleinman, M.; and Verrier, A. (2010). Guidelines for indoor air quality. *WHO Guidel.*, 9(454).
7. Yip, F.; Christensen, B.; Sircar, K.; Naehar, L.; Bruce, N.; Pennise, D.; … and Kapil, V. (2017). Assessment of traditional and improved stove use on household air pollution and personal exposures in rural western Kenya. *Environment international*, 99, 185-191.
8. Both, A.F.; Westerdahl, D.; Fruin, S.; Haryanto, B.; and Marshall, J.D. (2013). Exposure to carbon monoxide, fine particle mass, and ultrafine particle number in Jakarta, Indonesia: Effect of commute mode. *Science of the Total Environment*, 443, 965-972.
9. Badan Pusat Statistik. (2020). Hasil Sensus BPS : Jumlah Kendaraan Bermotor di Indonesia Tembus 133 Juta Unit. Retrieved December 5, 2022, from https://www.gaikindo.or.id/data-bps-jumlah-kendaraan-bermotor-di-indonesia-tembus-133-juta-unit/.
10. Haryanto, B. (2018). Climate change and urban air pollution health impacts in Indonesia. *Climate change and air pollution: The impact on human health in developed and developing countries*, 215-239.
11. Leung, D.Y. (2015). Outdoor-indoor air pollution in urban environment: challenges and opportunity. *Frontiers in Environmental Science*, 2, 1-7.
12. Cincinelli, A.; and Martellini, T. (2017). Indoor air quality and health. *International journal of environmental research and public health*, 14(11), 1286.
13. Abraham, S.; and Li, X. (2014). A cost-effective wireless sensor network system for indoor air quality monitoring applications. *Procedia Computer Science*, 34, 165-171.
14. Seguel, J.M.; Merrill, R.; Seguel, D.; and Campagna, A.C. (2017). Indoor air quality. *American journal of lifestyle medicine*, 11(4), 284-295.
15. Pavani, M.; and Rao, P.T. (2017). Urban air pollution monitoring using wireless sensor networks: A comprehensive review. *International Journal of Communication Networks and Information Security*, 9(3), 439-449.
16. Demir, A. (2015). Investigation of air quality in the underground and aboveground multi-storey car parks in terms of exhaust emissions. *Procedia-Social and Behavioral Sciences*, 195(216), 2601-2611.
17. Bernstein J.A.; Alexis, N.; Bacchus, H.; Berstein, I.L.; Fritz, P.; Horner, E.; … and Tarlo, S.M. (2008). The health effects of nonindustrial indoor air pollution. *Journal of Allergy and Clinical Immunology*, 121(3), 585-591.

18. Li, Z.; Wen, Q.; and Zhang, R. (2017). Sources, health effects and control strategies of indoor fine particulate matter (PM2.5): A review. *Science of the Total Environment*, 586, 610-622.
19. Tran, V.V.; Park, D.; and Lee, Y.C. (2020). Indoor air pollution, related human diseases, and recent trends in the control and improvement of indoor air quality. *International journal of environment research and public health*, 17(8), 2927.
20. Oh, H.J. and Kim, J. (2020). Monitoring air quality and estimation of personal exposure to particulate matter using an indoor model and artificial neural network. *Sustainability*, 12(9), 13-18.
21. Obaidullah, M., Dyakov, I.V.; Peeters, L.; Bram, S.;and De Ruycka, J. (2012). Investigation of particulate matter pollutants in parking garages. *Latest Advances in Biology*, *Environment Ecology*, 1, 105-109.
22. Pitarma, R.; Marques, G.; and Caetano , F. (2016). Monitoring indoor air quality to improve occupational health. *Advances in Intelligent Systems and Computing*, 445, 13-21.
23. Oh, C.S.; Seo, M.S.; Lee, J.H.; Kim, S.H.; Kim, Y.D.; and Park, H.J. (2015). Indoor air quality monitoring systems in the IoT environment. *The Journal Korean Institute of Communication and Information Sciences*, 40(5), 886-891.
24. Yick, J.; Mukherjee, B.; and Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks*, 52(12), 2292-2330.
25. Yi, W.Y.; Lo, K.M.; Mak, T.; Leung, K.S.; Leung, Y.; and Meng, M.L. (2015). A survey of wireless sensor network based air pollution monitoring systems. *Sensors*, 15(12), 31392-3142.
26. Handayani, A.S.; Pujiana, D.; Husni, N.L.; Amin, J.M.; Sitompul, C.R.; Taqwa, A. and Soim, S. (2018). Robustness of sensors network in environmental monitoring. *Proceedings of the 2018 International Conference on Applied Science and Technology (iCAST)*, Manado, Indonesia, 515-520.
27. Arroyo, P.; Lozano, J.; and Suárez, J.I. (2018). Evolution of wireless sensor network for air quality measurements. *Electronics*, 7(12), 342.
28. Manjunatha, P.; Verma, A.K.; and Srividya, A. (2008). Multi-sensor data fusion in cluster based wireless sensor networks using fuzzy logic method. *Proceedings of the 2008 IEEE Region 10 and the Third international Conference on Industrial and Information Systems*, Kharagpur, India, 1-6.
29. Gupta, G.S.; and Quan, V.M. (2018). Multi-sensor integrated system for wireless monitoring of greenhouse environment. *Proceedings of the 2018 IEEE Sensors Applications Symposium (SAS)*, Seoul, Korea (South), 1-6.
30. Handayani, A.S.; Husni, N.L.; Permatasari, R.; and Sitompul, C.R. (2019). Implementation of multi sensor network as air monitoring using IoT applications. *Proceedings of the 2019 34th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC)*, JeJu, Korea (South), 1-4.
31. Hautefeuille, M.; O'Mahony, C.; O'Flynn, B.; Khalfi, K.; and Peters, F. (2008). A MEMS-based wireless multisensor module for environmental monitoring. *Microelectronics Reliability*, 48(6), 906-910.

32. Naziha, A.; Fu, L.; Elamine, G.M.; and Wang, L. (2019). A method to construct an indoor air pollution monitoring system based on a wireless sensor network. *Sensors*, 19(4), 976.
33. Widodo, S.; Amin, M.M.; Supani, A.; and Handayani, A.S. (2020). Prototype design of CO_2, CH_4 and SO_2 toxic gas detectors in the room using microcontroller-based fuzzy logic. *Journal of Physics: Conference Series*, 1500, 012107.
34. Zuidema, C.; Sousan, S.; Stebounova, L.V.; Gray, A.; Liu, X.; Tatum, M.; … and Koehler, K. (2019). Mapping occupational hazards with a multi-sensor network in a heavy-vehicle manufacturing facility. *Annals of work exposures and health*, 63(3), 280-293.
35. Lee, D.D.; and Lee, D.S. (2001). Environmental gas sensors. *IEEE Sensors Journal*, 1(3), 214-224.
36. Fine, G.F.; Cavanagh, L.M.; Afonja, A.; and R. Binions, R. (2010). Metal oxide semi-conductor gas sensors in environmental monitoring. *Sensors*, 10(6), 5469-5502.
37. Adhao A.S.; and Pawar, V.R. (2018). Automatic cotton leaf disease diagnosis and controlling using raspberry Pi and IoT. In *Intelligent Communication and Computational Technologies: Proceedings of Internet of Things for Technological Development, IoT4TD 2017*, 19, 157-167.
38. Singh, S.K.; Rao, D.N.; Agrawal, M.; Pandey, J.; and Naryan, D. (1991). Air pollution tolerance index of plants. *Journal Environmental Management*, 32(1), 45-55.
39. Habibie, N.; Wiska, R.; Arshad, A..; Nugraha, A.N.; Diantoro, R.; Aini, I.F.; Halim, K.; Wisesa, H.A.; Wibisono, A.; and Jatmiko, W. (2016). CO_2 monitoring system for prototype of building air quality management using wireless sensor network. *International Journal on ICT*, 2(2), 49-60.
40. Mad Saad, S.; Andrew, A.M.; Shakaff, A.Y.M.; Mohd Saad, A.R.; Kamarudin, A.M.Y.; and Zakaria, A. (2015). Classifying sources influencing indoor air quality (IAQ) using artificial neural network (ANN). *Sensors*, 15(5), 11665-11684.
41. Dong, M.; Yang, D.; Kuang, Y.; He, D.; Erdal, S.; and Kenski, D. (2009). PM2.5 concentration prediction using hidden semi-Markov model-based times series data mining. *Expert Systems with Applications*, 36(5), 9046-9055.
42. Ali, S.; Tirumala, S.S.; and Sarrafzadeh, A. (2014). SVM aggregation modelling for spatio-temporal air pollution analysis. *Proceedings of the 17th IEEE International Multi Topic Conference* 2014, Karachi, Pakistan, 249-254.
43. Miao, Y.; Wu, H.; and Zhang, L. (2018). The accurate location estimation of sensor node using received signal strength measurements in large-scale farmland. *Journal of Sensors*, Volume 2018, Article ID 2325863, 1-10
44. Hyslop, N.P.; and White, W.H. (2009). Estimating precision using duplicate measurements. *Journal of the Air and Waste Management Association*, 59(9), 1032-1039.
45. Salfner, F.; Lenk, M.; and Malek, M. (2010). A survey of online failure prediction methods. *ACM Computing Surveys (CSUR)*, 42(3), 1-42.