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REAL-TIME DECISION SUPPORT SYSTEM FOR CARBON MONOXIDE THREAT WARNING USING ONLINE EXPERT SYSTEM

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Carbon monoxide (CO) pollution is a threat both to our health and well-being. CO concentration above safety threshold triggers serious illnesses that may even lead to death. Unfortunately, no system is yet capable of detecting and making decision online and in real-time concerning carbon oxide threat. Hence, decisions related to CO threat are often made late as they require expert analyses. This paper proposes a solution to this problem by developing a decision support system for CO threat using internet-based online measurement and an early warning system using cellular phone. Node station of CO sensor has been built using System on Chip (SOC) WIFI-Microcontroller capable of sending data via internet gateway. The pollution index value and the rule-based algorithm used to determine CO pollution categories in the web server program are in line with those stated in the Indonesia Air Pollutant Index (IAPI). Expert system programming based on expert knowledge is used to make decision on pollution. At the detrimental level, information is sent to users using a cellular phone. Results in this research show that the use of wireless sensor system integrated to the internet helps provide precise information on CO concentration that in turn, results in proper analyses using the expert system, in line with the regulations in place.

Key words: Online, Decision support system, Node station, Rule-based, Information

INTRODUCTION

Monitoring of air quality is very important as it affects both health and work safety. The level of carbon monoxide (CO) in the environment is one of the indicators for air quality. CO is colorless and it does not smell that it is hard to detect. At high concentration, CO is highly toxic and detrimental to health [01]. CO results from burning of fossil fuels by vehicles, industries, and open burnings [02, 03]. CO gets into the blood stream via the lungs and it ties with hemoglobin in the blood and taken by the Oxygen (O2) to cells. The consequence is less oxygen reaching body tissues and organs.

Healthy people who are exposed to high level of CO are at risk of reduced mental alertness [04]. Real-time monitoring of CO level is important in order to find out the air quality, as high concentration of CO is hard to detect by the human body [05]. Moreover, it is easily dispersed in open air. The width of coverage area is also another challenge for manual measurement. Therefore, the use of wireless sensor network really fits the need for environmental gas monitoring. Furthermore, wireless sensor technology has many merits including low cost, minimum maintenance, and wide coverage area [06].

Wireless sensor technology has been applied in many fields such as data fusion, data aggregation, sensing (temperature, air pressure), military applications, and environmental observation and monitoring. Wireless sensor allows measurement of environmental physical parameters in real-time [07]. Environmental monitoring requires the use of wireless sensor technology as the measurement is in the order of months and even years. Wireless sensor system allows data compression and prediction algorithm that the system built is of high efficiency [08].

Combining wireless sensor system with web based online technology enables the integration of sensors into a system that can be remotely accessed in real-time.The use of this system also helps to ease data communication as to improve performance [09]. Data processing can also be conducted remotely. Hence, it is more efficient in terms of cost than sending someone to go to monitoring points [10]. Wireless sensor technology can be built with and independent network independent from certain network providers. Some early warning systems have been implemented for natural disaster warnings such as soil deformation, water quality, earthquake, tsunami, and flood [11-15]. This early warning system is meant to prevent greater losses in terms of life, especially for events that cannot be directly detected by people.

Real-time microblogging is a data source that can be implemented in the early warning system named microblogging-monitoring system. Data input can be used for a decision support system using the knowledge-based framework. Combination of artificial intelligence techniques from high and low levels system analysis results in a system that is flexible and sustainable [16]. The rule-based method can also be implemented in the system. Entity identification can be recognized based on the already implemented knowledge based, that it helps categorizing messages. This resulting system has a high accuracy of information [17].

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The use of rule-based for decision support system in the wireless sensor network has also been implemented in the water source monitoring system. This system is capable of monitoring the contents of chemicalsubstances in the water. The use of rule-based method in this systemreduces computing load for large-scale systems [18]. Combining rule-based method with other systems like fuzzy, can also improve accurate prediction and speedy decision-making [19].

REALIZATION OF WIRELESS SENSOR SYSTEM

In this research, the system build consists of instruments placed in the field and known as a node. Thisnode functions to conduct data acquisition of carbon monoxide concentration and send those data via the internet. This device continuously sends data to a website using broadband internet access provided by a WIFI-GSM modem to the web server database for storage and management [20]. On the webserver, an online database has been created and a receiver and storage application scripts have been written. Data communication verification is done by giving feedbacks and validating data, as to avoid error and redundancy. An overview of a network system is shown in Figure 1.

A rule-based expert system programming algorithm is developed in the internet web hosting to make decisions on the conditions of carbon monoxide concentration. This system performs two computations using the rule-based algorithm. First, rule-based forward chaining to determine categories of pollution levels and rule-based expert system to determine conditions to automatically trigger the early warning system. The rule-based expert system uses danger status set earlier by environmental AND/OR disaster experts. The output of the rule-based system is information data that are accessible with computers or warnings sent to mobile phones.

RULE-BASED SYSTEM DEVELOPMENT

This research employs the method of rule-based forward chaining from a computer application developed at a web host. Data of CO concentration is automatically put into the web host database via an acquisition and communication system connected to the local database. The rules from The Indonesian Air Pollutant Index (IAPI) that categorizes pollution levels are put into the rule database. Rules from experts are also put into the database and they serve as the knowledge based. Both databases are thenput into and managed by the website administrator. A diagram of the rule-based system is given in Figure 2.

Rule-based Reasoning System

The computer application in this research uses the rule-based system as it fits all scopes of problems in computer programming. This system solves problems based on bits in a set of rules. A reasoning process is rerun prior to another reasoning process even though the earlier one has been finished [21]. In general, rules state what must and must not be done depending on the situation. Rules have a typical format:

If <conditions> then <conclusion

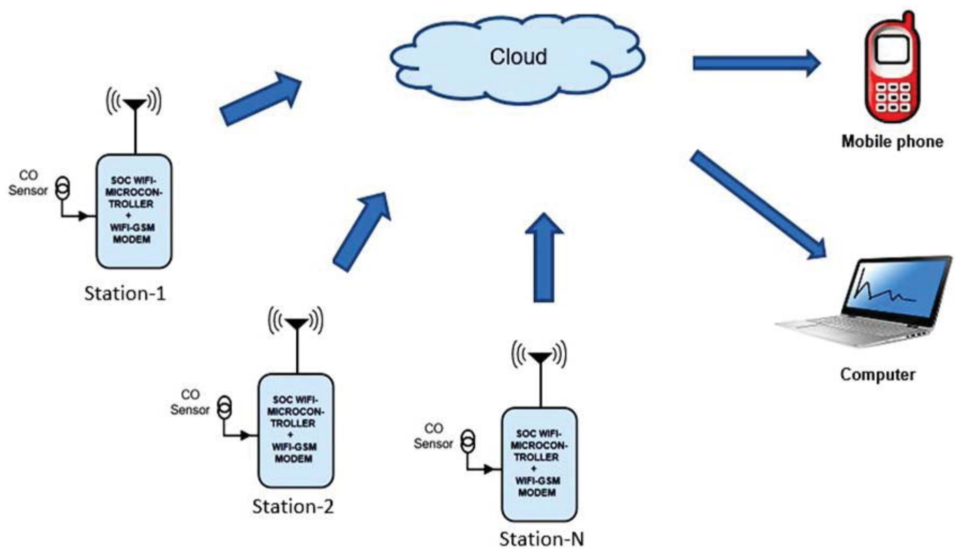

Figure 1: Carbon monoxide network for the online system

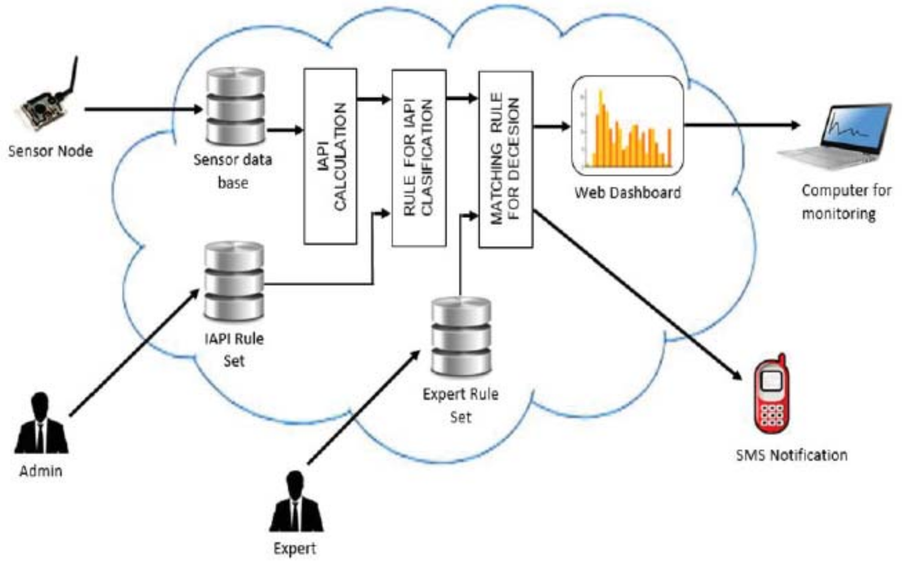

Figure 2: Diagram of web-based rule-based system

The rule-based reasoning in this system is an algorithm to solve a problem that uses knowledge from an application domain in the form of rules. There are two possible methods of reasoning; forward chaining and backward chaining. In forward chaining, problem description is taken from a working memory as a set of conditions and solutions will be found for them. Once a solution is found, all matching conditions that fit the ones in the working memory are sought. The results will provide a set of rules that can be applied to find solutions for those problems. This set of rules is called a conflict set.

Rule-based reasoning technique uses a strategy of conflict resolution by choosing one rule from a set of rules. This chosen rule is applied to find the right solution to the problem. The content of the working memory is then subsequently updated based on that solution. The search for rules ensues as the working memory is kept on updated, and the reasoning process proceeds based on the new matching rules. This process continues until all required solutions are gained and there are no more rules left that fit the ones in the working memory.

Backward chaining is the same as forward chaining in most of the processes. The main difference is in taking problem descriptions as a group of conclusions from a condition, and trying to find the premises based on those conclusions. This means finding rules that fit with all or most of the conclusions in the working memory. On the other hand, forward chaining is a conflict resolving strategy by choosing one rule from oneset of applicable rules. The Indonesian Air Pollutant Index (IAPI) is a set of analysis used to simplify information on air pollution agents in which CO is also listed. The values in the IAPI categories are based on the Decree of the State Minister for the Environment No. KEP-45/MENLH/I0/1997. The rules set in the IAPI category are shown in Table 1.

Table 1: Rules used in the reasoning system

Rule	Statement
1	IF (CO input concentration ≤ 50 μg/m^3) THEN Category is Good
2	IF (CO input concentration 51 μg/m^3 to 100 μg/m^3) THEN Category is Medium
3	IF (CO input concentration 101 μg/m^3 to 199 μg/m^3) THEN Category is Unhealthy
4	IF (CO input concentration 200 μg/m^3 to 299 μg/m^3) THEN Category is Very Unhealthy
5	IF (CO input concentration ≥ 300 μg/m^3) THEN Category is Dangerous

Rule-based Expert System

For the needs of an early warning system, rules from environmental experts will also automatically be used. Rulings from those experts will be put into the knowledge-based system in the host website. This part requires informed decision from environmental experts to be used as knowledge for the rule-based system. These experts are from the State Ministry for the Environment who has expertise in disaster management. These knowledge-based rules on the early warning of CO pollution include:

1. If there are two detections of a value of ≥ 300 of IAPI within 3 measurements, the system will automatically give a warning alert.
2. If the IAPI value is ≥ 101, the system will automatically give a warning alert.

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3. If the IAPI values is < 101, will not give or will stop giving a warning alert.
4. A warning alert is a repeated alarm every 30 minutes until the IAPI value is < 101

Those four statements from the experts serve as the foundation to make the rule that determines the warning s sent later concerning monoxide carbon. These warning s are sent to the public using the Short Message Service available on cellular phones.

RESULT AND DISCUSSION

Result of the application of online and real-time rule-based system for environmental carbon monoxide monitoring using wireless sensor system can be accessed via the internet. The data that can be accessed from the internetinclude; map of sensor location, acquisition time, concentration value, and status of air pollution index. Measurement results of carbon monoxide concentration are kept in the database of a web server and are shown real-time as graphs. Figure 3 depicts results of CO measurements at 5 sensor nodes in real-time. The graph in Figure 3 explains changes in CO concentration with time. The lowest concentration was detected in the early morning. The highest concentration is for 4:00 PM, at 16.2 μg/m^3. In general, carbon monoxide concentration is higher during the day, compared to the figures during the night.

The values from online and real-time CO concentration monitoring are displayed in numbers, fluctuating graph, and indicator panel. Data communication system is tested for transmission time between the sensor node and the online web server for every data given an ID code. This dashboard displays calculations that meet the IAPI rule using the following formula:

$$I = \frac{I_A - I_s}{X_A - X_S}(X_X - X_B) + I_B \tag{1}$$

Where I is calculated IAPI, IA is the Standard Index of Air Pollution (ISPU) upper limit, IB is the ISPU lower limit, XA is the ambient upper limit, XB is the ambient lower limit, and XX is the ambient measurement result. Results of calculations that adhere to the IAPI rule do not only yield index numbers but also statements of conditions and reporting colors in line with the IAPI. Calculation results are not only used to make statements of conditions and reporting displays but also model rule number 2 that will be used for the early warning of detrimental CO concentration. This warning is based on the rules set by the experts.

Those results show that a warning is not only based on calculations resulting from IAPI rules, but also from statements from experts written in the knowledge based. This system reveals that certain categories of IAPI may result in different warning conditions. This is due to the effect of knowledge based set by experts that requires three readings of the same IAPI value to be worthy of a warning for instance.

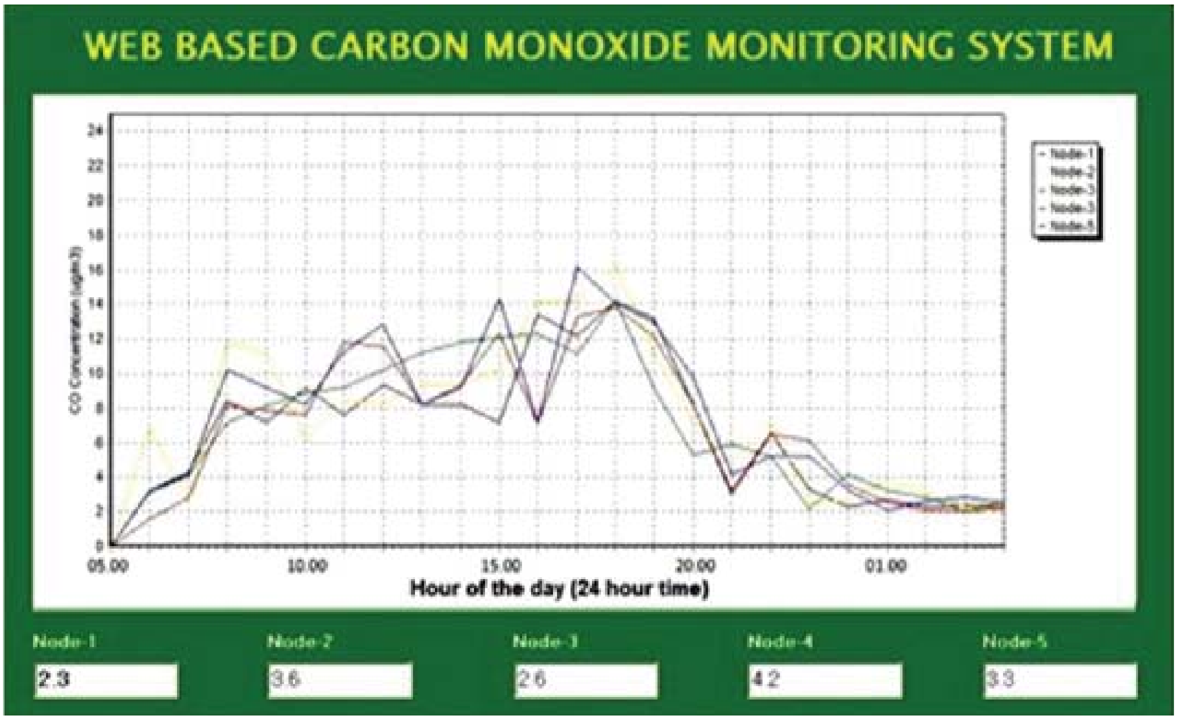

Figure 3: CO measurement at sensor node as displayed in real-time

This research performed validation for the rule-based system by manually recording measurements and compare them with calculations by the system built. Validation covered values from low to high concentration of CO that it properly represented measurements carriedout by the rule-based system. Resultsof this validation process are given in Table 2.

These results were compared to those from standard (manual) measurements. It was subsequently confirmed that both rule-based calculation and manual measurements yield similar results for various ranges of carbon monoxide concentration. Hence, the system can be used. Testing for data transfer rate (throughput) from sensor node to web server has been conducted to figure out data communication effectiveness. This is very important as it affects system response for data reception, rule-based execution, and warning of measured CO concentration.

Testing results for each node are given in Figure 4. They show that on average, data transfer rate from sensor node to web server is 764 milliseconds. It can also be seen that the highest transfer rate is between mid-night and early morning, whereas the highest delay time is experienced in the afternoon. Each sensor node comes with different data transfer rate performance. This is also influenced by GSM network bandwidth, signal strength, and Network traffic, among others.

Testing for warning time was carried out by giving markers from the time data are acquired by the WIFI-Microcontroller to the moment warning s are received by cellular phone. This testing also took consideration of network traffic of the internet and the cellular phone. Testing results for each sensor node are given in Figure 5. It can be seen that the average warning rate for all networks is 15.6 second, which is still very effective for early warning of carbon monoxide threat. As in the case for data transfer rate testing, differences in sensor node performance are affected by GSM network bandwidth, signal strength, and Network traffic.

Table 2: Results of rule-based system validation against standard measurement

Node ID	Developed system measurement (μg/m^3)	IAPI (μg/m^3)	Category (Rule based system)	Reference measurement (μg/m^3)	Validation Statement
Node-1	4.27	44	Good health effect	4.35	True
Node-2	8.10	79	Medium health effect	7.85	True
Node-3	19.85	217	Very unhealthy effect	20.10	True
Node-4	36.60	322	Dangerous healthy effect	37.01	True
Node-5	10.95	114	Unhealthy effect	10.23	True
Node-1	6.20	62	Medium health effect	6.35	True
Node-2	5.35	54	Medium health effect	5.15	True
Node-3	1.60	16	Good health effect	1.22	True
Node-4	49.35	429	Dangerous healthy effect	47.75	True
Node-5	20.00	218	Very unhealthy effect	19.52	True

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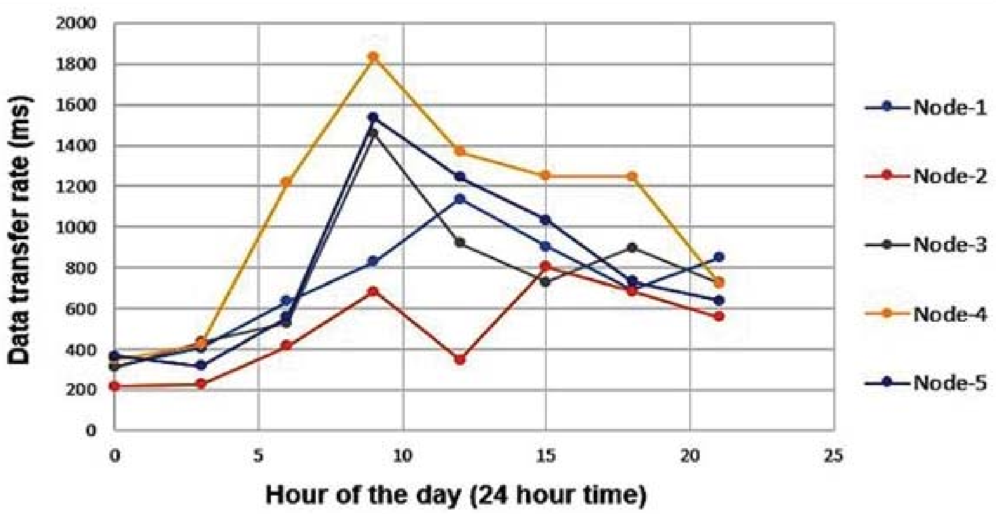

Figure 4: Results of testing for data transfer rate from sensor nodes to the web server

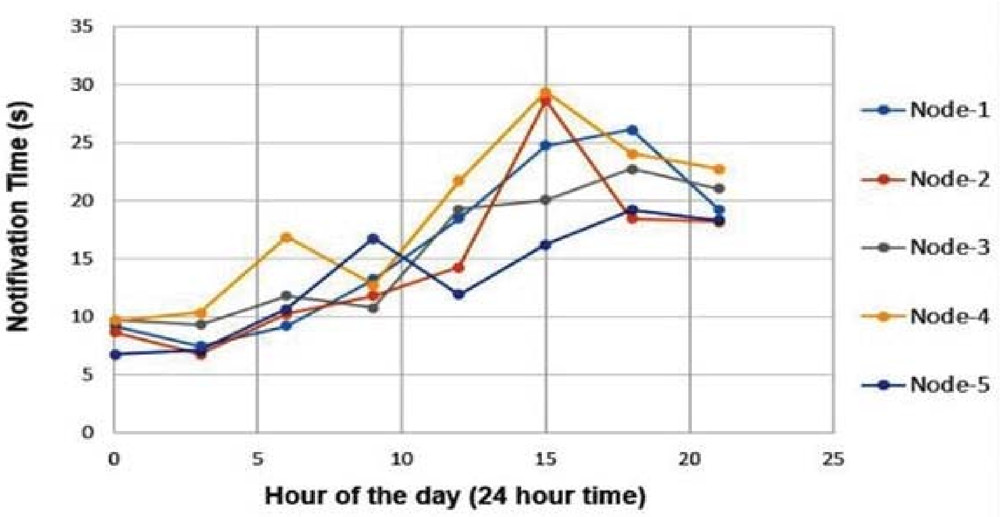

Figure 5: Results of testing for warning time from sensor nodes to the cellular phone

CONCLUSIONS

The online web-based rule-based system has been proven to be effective and speedy in making decision concerning CO concentration in the environment using data from wireless sensor nodes. Data of CO concentration in the environment can be acquired both online and in real-time using the internet. The rule-based system allows such data to be managed in line with the regulation observed in a country and the results to be used in determining categories of air pollution. Rule-based system to evaluate CO concentration can also be combined with a knowledge basedsystem set by environmental experts. Both expert knowledge based and rule-based index from IAPI can be utilized to provide an early warning system of the danger of carbon monoxide. Validation of calculations from the rule-based system against those of standard measurement was carried out and its efficacy has been confirmed. This system has successfully sent data from classifications and expert analyses in a timely manner via cellular phone warning. Therefore, this system can readily be utilized.

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