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Development of a smart system for gasoline car emissions diagnosis using Bayesian Network

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Abstract

A vehicle exhaust emissions test is an activity carried out to determine the content of the remaining combustion products that occur in the fuel in the vehicle engine. Many people do not understand exhaust gas content from emission tests, so to make this easier, this study aims to create a smart application that can diagnose vehicle emissions quickly and accurately using the Bayesian Network (BN) algorithm. Application development begins with BN modeling using the MSBNx application until the appropriate results are achieved. Validation of the BN structure that has been designed with various inputs is *carried out to ensure that the BN modeling is correct. The next step is to compile the BN modeling algorithm in the MATLAB application so that it becomes a system that can process input in the form of measurement results for Toyota car emissions. The new BN model for vehicle emission gas diagnosis has been successfully constructed. The results of the system reading when there is an HC content of 217 ppm, the probability value of bad emissions increases to 63.5%. Of the 10 tests performed, the system was able to diagnose them all correctly.*

Keywords:
Bayesian Network;
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Gasoline;
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INTRODUCTION

The total population of Indonesia is 268 million people, currently, more than 55% own a motorized vehicle, be it a motorcycle or a car. Therefore, the fuel needed and the need for maintenance of the engine are also very important [1]. The increasing number of engine vehicles in Indonesia will affect or pollute healthy air conditions into unhealthy air conditions in the environment, this happens because the exhaust gases generated in these engine vehicles contain unhealthy gases such as carbon monoxide (CO), hydrocarbons (HC), and others. It is conceivable that more than 55% of the Indonesian population currently owns a motorized vehicle, especially a car, and does not know how to diagnose the exhaust emission test results, resulting in a lack of awareness to carry out routine maintenance properly. The need for good air conditions, namely oxygen, is currently getting worse and depleting for Indonesia and the world [2, 3, 4, 5].

The vehicle emission test is the residual combustion product from the fuel in the vehicle engine that is released through the engine exhaust system, while the combustion process is a chemical reaction between oxygen in the air and hydrocarbon compounds in the fuel as a power producer [6, 7, 8]. Exhaust emissions from motor vehicles are the main source of air pollution originating from transportation as well as the work of the combustion engine of the motor vehicle. The results of this emission test can also be used to determine if there is damage to the engine parts of the vehicle, and to adjust the air and fuel mixture properly.

Currently, in conducting vehicle exhaust emission tests, many do not know about the benefits of the data obtained in the emission test, while in the treatment the data obtained are very large. To make it easier for the general public to know the data obtained from the emission test, the authors aim to implement a Bayesian Network (BN) to diagnose the emission measurement results [9][10]. This BN as using the previous statistical information was then successful in many practices and uses and implementation. The BN method is used in research because this tool is very suitable in giving a decision from a certain indication. BN's decision is to process data from a trained repository which will then be retrieved with cross-validation data. BN is a probability-based data modeling method that represents a set of variables and their conditional dependencies through a Directed Acyclic Graph (DAG). Each node that is formed in the graph has a Conditional Probability Table (CPT) [11, 12, 13, 14].

BN provides a useful tool because it represents a probability relationship between a cause and a symptom or between a symptom and an error. It can also represent a multi-fault and multi-symptom model [15, 16, 17, 18, 19, 20]. In addition, it can effectively analyze the complex causal relationship between the BN node by its inference and sensitivity method. In addition, the structure of the causal network can be adapted flexibly by simply adding nodes and arcs to the existing BN model [21]. Although several BN based approaches such as El Amrani [22] and Li [23] have been previously developed for inference of diagnostic results, there are still limitations in developing network modeling for diagnosis of BN based emission measurement results. In this study, we apply BN for emission data identification, emission diagnosis inference, and analysis of accuracy in reading Toyota car emission measurement results [24, 25, 26, 27].

Based on the importance of knowing the value of vehicle emissions and the ability of the BN method in making decisions, we aim to create a smart application to diagnose the measurement results of Toyota car emissions using the BN method.

METHOD

Based on the input data obtained, the probability value will be calculated through several stages using the BN method, starting from determining the parameter value for each emission content, then determining the conditional probability value, after two values are obtained, the system will calculate the combined and posterior probability values for each emission condition. adjusted for the BN structure and the posterior probability value is used as a probability inference of the merits of the emission. The BN generates relational information and conditional probabilities through bidirectional propagation between input and output nodes. Also, in real case implementations it is common to use multistate nodes. So, from the input made by the user, the result will be in the form of emission conditions.

Application design can be divided into several stages. In general, the stages are preparing the concept of an algorithm scheme, modeling BN according to the emission diagnosis concept, making a program in MATLAB, and testing the system that has been made. BN is validated by providing input variations to ensure that the probability value and network structure are correct. The input node is made to find out the data or content in the exhaust emission test for examples of O2, HC, CO2, CO and Lambda. Then after making the input node, a node is made for the diagnosis of the emission test, for example the things or impacts that occur from the air content or whether the emissions are good or not. Furthermore, if each node has been created then each node is connected. Then after being connected, the probability value is entered into each node, whether it is an input or output parameter, this aims to make the data as a reference for the emission test. After completion, the graph on each node and the evaluation of each node can be seen.

The emission limit refers to the ministerial regulation no. 05 of 2006 concerning the threshold for old motor vehicle exhaust emissions for gasoline engine cars produced above 2007 as shown in Table 1.

For the record, the parameters of the exhaust gas emission threshold in Indonesia are based on the parameters of carbon monoxide (CO) 1.5% and hydrocarbons (HC) 200 ppm. Vehicle emissions can also indicate problems that occur in car engines [28][29].

Bayesian Network Structure

The MSBNx application is used to create an initial BN model until the appropriate results are obtained, as shown in Figure 1. At the time of the emission test, the input and output parameters were carried out based on the concept of vehicle exhaust emission diagnosis, especially from the Toyota brand.

Table 1. Threshold of Emission

Particle	Threshold
CO	≤ 1.5%
CO_2	> 12%
HC	≤ 200 ppm
O_2	≤ 2%
LAMBDA	1

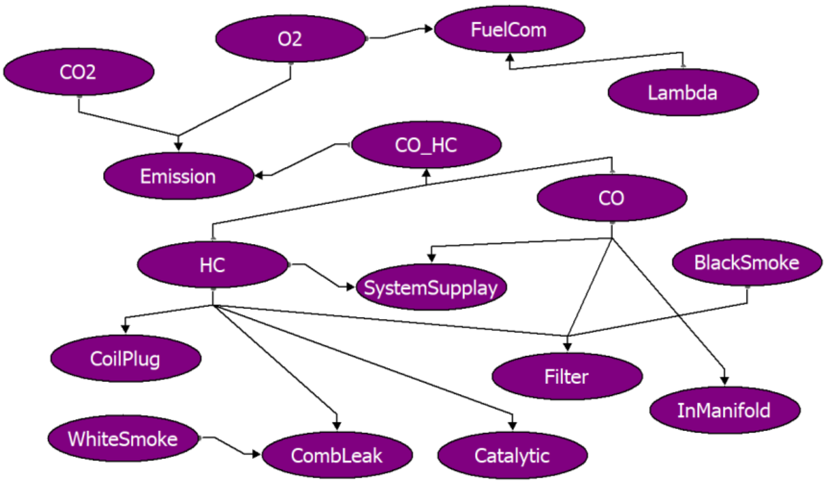

Figure 1. Bayesian Network Structure

The network consists of 16 nodes with 7 nodes as input and 9 nodes as output. HC and CO nodes are the dominant determinants of emission results. If one of the HC and CO has a value that exceeds the threshold then the emission results will be bad, so in practice, HC, and CO before entering the Emission node first enter the connecting node, namely the CO_HC node. Indication of damage to vehicle components based on input values. For example, if the HC input value exceeds the threshold, it will affect the CoilPlug and SystemSupplay nodes. Hydrocarbon air content is a very important thing in conducting vehicle emission tests, because the content is the result of whether a vehicle engine is good.

Hydrocarbon is a gas that indicates the remaining gasoline that is wasted with vehicle exhaust fumes. Hydrocarbons have an ideal value that should not exceed 200 ppm. If getting a result that is far from the ideal value, it will result in engine power getting tired easily, then wasteful fuel consumption. The HC content can be high because of the incomplete combustion of fuel in the engine combustion chamber. Not only the fuel combustion factor, but the leakage of oil that enters the combustion chamber also contributes to increasing the HC content. Another possibility is that the coil component begins to weaken due to the age of the car and its electrical capabilities so that the spark plug performance is not optimal. Apart from HC nodes, the percentage of System Supply nodes is also affected by the CO value.

Prior Probability

The first step after the formation of BN is to determine the prior probability value for each node which is the input parameter. These nodes are referred to as parent nodes, namely the nodes at the top layer. The percentage determination as shown in Table 2 is based on actual conditions that usually occur during emission tests.

Conditional Probability

When the prior probability value is completed, the next step is to provide a conditional probability value or what is called the Conditional Probability Table (CPT) in each appropriate column. The percentage value given must be in accordance with the concept of vehicle exhaust emission diagnosis. The CPT for the Emission node can be seen in Table 3. It can be seen in the table that the nodes connected to the Emission node are CO2, O2, and CO_HC. Where the CO_HC node is the connecting node for the CO and HC nodes. If BN accepts the input value of CO2 is greater than or equal to 12%, O2 is less than or equal to 2%, and CO or HC is of good value, then the result of good emission is 95% and bad emission is 5%.

Table 2. Prior Probability

Node Name	Event	Precentage (%)
HC	HC ≤ 200 ppm	80
	HC > 200 ppm	20
CO	CO ≤ 1.5%	80
	CO > 1.5%	20
CO^2	CO^2 ≥ 12%	80
	CO^2 < 12%	20
O^2	O^2 ≤ 2%	80
	O^2 > 2%	20
Lambda	λ ≥ 1	40
	λ < 1	60
White Smoke	Yes	20
	No	80
Black Smoke	Yes	20
	No	80

Table 3. CPT of Emission

Parent Node (s)			Emission (%)	
CO^2	**O^2**	**CO_HC**	**Good**	**Bad**
$CO^2 \geq$ 12%	$O^2 \leq$ 2%	Good	95	5
		Bad	30	70
	$O^2 >$ 2%	Good	80	20
		Bad	20	80
$CO^2 <$ 12%	$O^2 \leq$ 2%	Good	80	20
		Bad	20	80
	$O^2 >$ 2%	Good	70	30
		Bad	10	90

Table 4. CPT of Filter

Parent Node (s)			Filter (%)	
Black Smoke	**CO**	**HC**	**Good**	**Bad**
Yes	CO ≤ 1.5%	HC ≤ 200 ppm	40	60
		HC > 200 ppm	30	70
	CO > 1.5%	HC ≤ 200 ppm	20	80
		HC > 200 ppm	10	90
No	CO ≤ 1.5%	HC ≤ 200 ppm	95	5
		HC > 200 ppm	40	60
	CO > 1.5%	HC ≤ 200 ppm	40	60
		HC > 200 ppm	30	70

Because the percentage value of good emissions is greater than bad emissions, the conclusion is that the results are good emissions.

From each value given to the CPT will update the BN probability value for each associated node. It is necessary to ensure that each accumulated percentage is in accordance with the intended conditions.

Table 4 shows the CPTs for the filter nodes connected to the BlackSmoke, CO, and HC nodes. Dirty filters are usually marked by black smoke coming out of the car exhaust. The malfunction of the filter components can also cause high values of HC or CO in exhaust gas emissions. Based on this concept, then applied to the CPT for filter nodes to support the BN system. If the car does not emit black exhaust gas, CO is less than or equal to 1.5%, and HC is less than or equal to 200 ppm, the filter components are indicated to be in good condition.

RESULTS AND DISCUSSION

In ensuring that the designed system can function properly, a discussion on the results of making an intelligent vehicle exhaust emission diagnostic system is introduced in this chapter. It is explained in detail about how the system works in analyzing emission data using the capabilities of the BN methodology so that it can produce important information about the condition of the vehicle. The results of the analysis are then documented in the form of an interface design so that it is easy to understand. BN with multistate node is applied for vehicle engine performance diagnosis based on its emission.

Research on the implementation of BN in creating intelligent applications to diagnose vehicle exhaust emissions has been successfully carried out.

Bayesian Belief Update

The probability percentage update in the absence of evidence is shown in Figure 2. The distribution of the percentage values for good and bad vehicle conditions is 50% each. Before any evidence enters the JB system, there is no indication of a problem. This is expressed by the percentage value of good condition more than or equal to 50%. This percentage value is the basis for the system to decide the type of problem that occurs in the vehicle.

All percentage values change when the system reads the presence of HC elements beyond the maximum limit as shown in Figure 3. The percentage value of good emissions is less than 50, this indicates bad vehicle emissions. The graph also shows some indications that cause bad emissions. The system recommends catalytic checks, coil plugs, combustion chamber leaks, and fuel lines to the combustion chamber. The updated percentage value will change according to the state of the vehicle's emission gas.

Validation of the System

In the implementation of this study, we did not collect data for direct vehicle emission testing but only obtained data from existing references, as shown in Table 5. These data were obtained from gasoline cars that had carried out emission tests, located at the Auto2000 Rajabasa workshop in Bandar Lampung on October 24, 2020, at 13.16 WIB.

Application interface design as shown in Figure 4. When the user operates, they will be asked to enter data in the form of HC in ppm, CO percentage, CO2 percentage, O2 percentage, Lambda, and the color of the smoke coming out of the exhaust. After the input is complete, the user is required to click the start button.

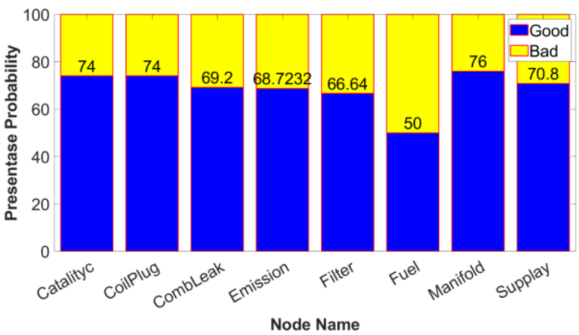

Figure 2. Probability Updates without Evidence

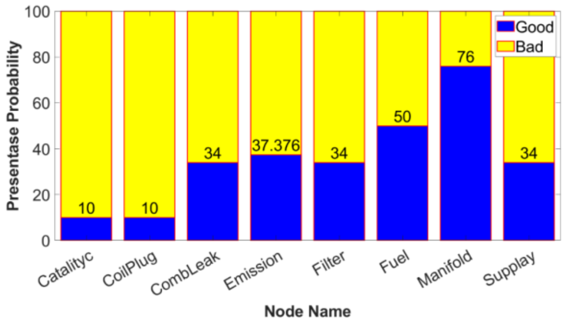

Figure 3. Probability Updates with Evidence

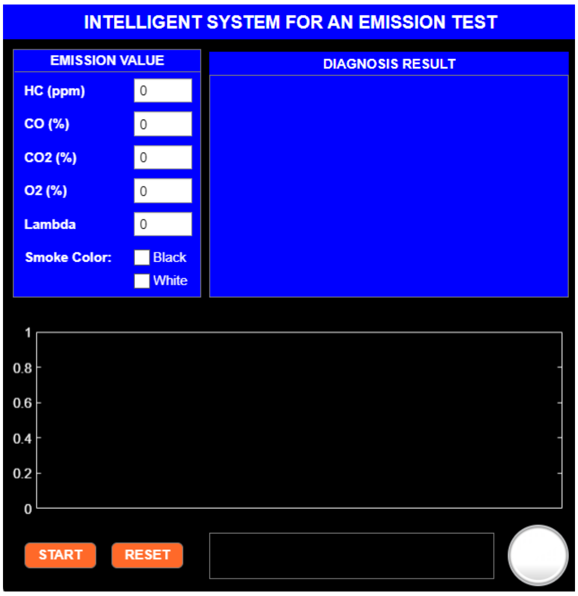

Figure 4. App Initial View

This software will immediately display the emission conditions and is supported by an indicator light. The indicator light is red if the emission is bad, while when the emission is good it will be green. This application is also equipped with a reset button which functions to clean data that has been previously entered.

The experiment was carried out with 200 ppm HC data, 1.5% CO, 12% CO2, 5% O2, Lambda 1, and colorless smoke. The results show emissions are in good condition with a percentage of 77% and there is no indication of problematic vehicle components, as shown in Figure 5. In the diagnostic results column, all were stated to be good. This result is in accordance with the theory and emission limit standards which can be seen in Table 1.

In the emission data number 4, 6, 7, 8, and 9, the hydrocarbon capacity has exceeded the good condition limit as shown in Table 5. Emissions tests on numbers 4, 8, and 10 contain carbon monoxide which have also exceeded the threshold.

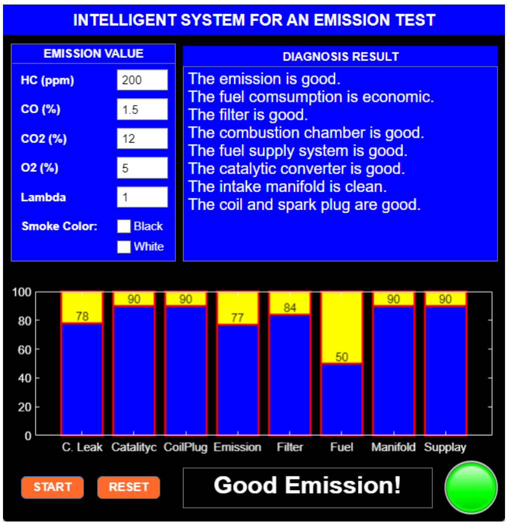

Figure 5. App Display with Good Emission Data

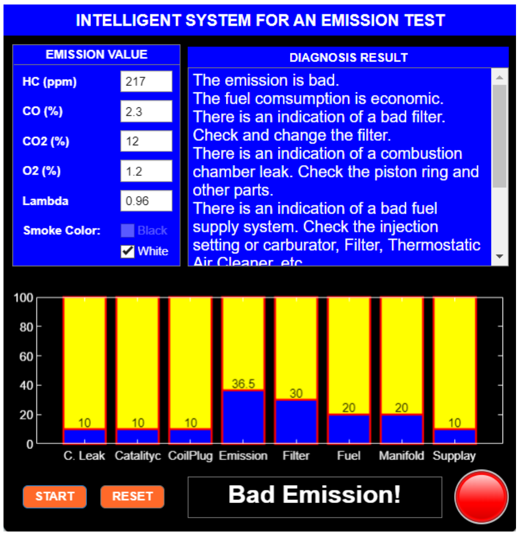

Figure 6. App Display with Bad Emission Data

The system output results are correct, emission tests number 4, 6, 7, 8, 9, and 10 are read by the system as bad emissions. Meanwhile, emission tests number 1, 2, 3, and 5 are read by the system as good emissions. Emission data measurement using Bayesian Networks-based system is more effective in terms of time than reading the emission measurement results manually. Input data with emission content include HC = 217 ppm, CO = 2.3%, CO2 = 12%, O2 = 1.5%, Lambda = 1, and white smoke.

The results of the system diagnosis indicate poor emission conditions and are supported by indications of damage to vehicle parts as shown in Figure 6. Bad emission gas with a percentage of 100% - 36.5 = 63.5%. These results are in accordance with the determination of values when modeling Bayesian networks.

Table 5. Data Validation

No. of Data	Particles	Values	Vehicle Types	Results by System
1.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	1.43 % 38 ppm 6.1 % 20.90 % 2	Toyota Kijang Innova 2018	Good Emission
2.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	0.49 % 75 ppm 9.0 % 6.85 % 1.078	Toyota Avanza 2017	Good Emission
3.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	6.05 % 45 ppm 2.3 % 16.84 % 2.000	Toyota Calya 2019	Bad Emission
4.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	5.15 % 250 ppm 3.7 % 10.65 % 1.508	Toyota Agya 2018	Bad Emission
5.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	0.00 % 21 ppm 15.0 % 1.27 % 1.011	Toyota Fortuner 2017	Good Emission
6.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	0.70 % 500 ppm 11.0 % 2.45 % 0.750	Toyota Avanza 2006	Bad Emission
7.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	0.54 % 400 ppm 12.0 % 3.0 % 0.400	Toyota Kijang Krista 2000	Bad Emission
8.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	2.15 % 250 ppm 6.0 % 2.3 % 1.200	Toyota Rush 2008	Bad Emission
9.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	0.70 % 600 ppm 7.2 % 1.80 % 0.850	Toyota Kijang Innova 2007	Bad Emission
10.	Carbon Monoxide (CO) Hydrocarbons (HC) Carbon Dioxide (CO_2) Oxygen (O_2) Lambda	2.45 % 80 ppm 8.0 % 2.5 % 1.800	Toyota Agya 2012	Bad Emission

A series of vehicle emission gas data tests were carried out to ensure the system was functioning properly. There are 10 test data, each of which has five emission elements, namely Carbon Monoxide, Hydrocarbons, Carbon Dioxide, Oxygen, and Lambda. There are two elements that are dominant determinants for whether the results of vehicle exhaust emissions are good. Hydrocarbons and Carbon Monoxide are gases that are harmful to the body and their thresholds serve as benchmarks for system decision makers.

CONCLUSION

A Bayesian network-based system for vehicle emission diagnostics has been successfully developed. The application of Bayesian networks in intelligent system design begins with the creation of a network model. The MSBNx application is used to generate emission percentages based on the value of each state. The percentage results collected are used as a reference when building a Bayesian network algorithm in the MATLAB application. It also provides the ability to enter data that will be used as a basis for calculating the percentage of emissions and engine condition in the system. Furthermore, the application development uses the App Designer menu so that the system can be installed on each computer and is easy to operate.

The Bayesian network model was successfully built based on the concept of vehicle emission analysis. The emission measurement results using a Bayesian Networks-based system are superior in terms of time when compared to reading the emission test results manually. The network consists of 16 nodes with 7 input nodes and 9 output nodes. The 16 nodes are connected according to their function so that it becomes a system capable of diagnosing vehicle emissions. According of ten tests using different data, all data entered can be predicted quickly and accurately by the system. All software features also work fine.

It is advisable to embed the system with a control device connected to the emission gas sensor so that actual results are obtained. It is necessary to adapt the program to the controller base used. It is necessary to design an appropriate emission device model for the housing of all components.

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