## ROAD PAVEMENT CONDITION MODELLING AND PREDICTION USING BAYESIAN NETWORK

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#### Abstrak

Road deterioration is caused by poor structure, poor drainage, climatic or geological effect and loading. The existing models for condition prediction can be categorized into three main groups, namely deterministic models, probabilistic models and Bayesian models. Among them, one of the most commonly used discrete time stochastic process models is the Markov Chain (MC) model. However, it has limitations that cannot renewedroad deterioration factors in real time. This research can minimize the limitation of Markov Chain using prediction model, which is more real time because it is considered by the road damage factors and conditional dependence relationship of the factors.

The architecture design of proposed model using Bayesian Network. The proposed model requires Static Bayesian Network (BN). Static Bayesian Network identifies factors responsible for pavement failure and conditional dependence relationship of the factors. In creating a model, there are two sources of information used namely expert knowledge and historical data.

The purpose of this research is to develop road deterioration model for predicting future road condition in national road network on the national road of Batas Kota Caruban – Batas KabNganjuk. The prediction results showed that the road condition in next year is 51 % in a good condition, 44 % in a moderate condition, 3 % in bad condition and only 1 % in a very bad condition. Value road conditions increased by 14 % compared to the previous condition. The prediction result of this model can be used to prepare roadmaintenance plan. In addition, this model will improve an effective maintenance optimization.

# INTRODUCTION

Over the last several decades due to increasing number of vehicles, a large number of road infrastructures for transport have been built. The sustainable maintenance of these roads has been drawing increasing attention recently because of constrained budget funding and ineffective maintenance. The ineffective maintenance of these roads increases the road deterioration. Road deterioration is caused by poor structure, poor drainage, climatic or geological effect and loading.

Predicting deterioration is a vital component of pavement management systems. The ability of road deterioration models to predict future condition determines the quality of maintenance decision. The existing models for condition prediction can be categorized into three main groups, namely deterministic models, probabilistic models and Bayesian models. Among them, one of the most commonly used discrete time stochastic process models is the Markov Chain (MC) model. However, it has limitations that cannot renewed road deterioration factor in real time. This research can minimize the limitation of Markov Chain using prediction model which is more real time because it is considered by the road damage factors and conditional dependence relationship of the factors.

This paper proposed a model using Bayesian Network (BN) for road pavement condition using Software Genie 2.0. This research will be applied to the data collected from Batas Kota Caruban – Batas Kab Nganjuk.

## **BN THEORY**

Bayes' Theorem is a theorem of probability theory originally stated by the Reverend Thomas Bayes. Bayesian networks, also known as Bayesian belief network or belief networks, are a modelling technique for causal relationship based on Bayesian inference. A BN contains two key aspects. The first is a graphical representation of the dependencies between variables. A directed acyclic graph (DAG) is used to represent this. Each variable is represented by a single node within the graph. Direct causal dependencies are represented by a directed arc from the "causing" node to the node that is affected.



Fig 1. Simple Bayesian Network

The second aspect of the network is a collection of conditional probability tables (CPT's) which represents the probabilities of each state of a node occurring given the states its parents may take. The strengths of relationships represented by directed arcs can be modelled in the probability values stored within the conditional probability tables associated with each node. These values are used to infer the posterior probabilities of each variable given those of its parents.

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	Temperature	Cold	Cool	Hot
	No		0.33333333	0.85714286
	Yes	0.5	0.66666667	0.14285714

Fig 2. CPT (The rows represent the outcomes of the variables, the columns represent the parents)

To develop a structure of bayesian network, we need :

- 1. Variables/ Nodes for X<sub>1</sub>, X<sub>2</sub>...X<sub>n</sub>
- 2. Relationship between the variables
- The probability of variablesthere are P(Xi|Pa(Xi)) for i=1,..., n

One distinctive advantage of BN is its inference ability in calculating beliefs of events based on new observed evidence. The beliefs (probabilities) are updated in accordance with observation using Bayesian updating.

#### GENIE 2.0

GeNIe is the graphical interface to SMILE, a fully portable Bayesian inference engine developed by the Decision Systems Laboratory and thoroughly tested in the field since 1998. GeNIe 2.0 is the latest version of GeNIe.

#### **METHODS**

This study takes a case study on the national road of Batas Kota Caruban – Batas KabNganjukwith a total length of 14.16km.Batas Kota Caruban – Batas KabNganjuk is the middle of the traffic lane that connect East Java Province with the Central Java Province.

The data used in this study was using secondary and primary data. Secondary data obtained through data collection and literature review. Data collection derived from Satuan Kerja P2JN East Java province in the 2014 to be used to predict the condition of pavement in 2015.Primary data obtained through interview, survey and questionnaire.

The study consists of two types of questionnaires : (1) questionnaire 1 for evaluating the effect level of factors on road deterioaration; (2) questionnaire 2 for identifying cause- effect relationships among the identified factors; (3) questionnaire 3 for determine CPT among variables

Framework of this study are as follows:

1) The first stage, literatur review to identificate a set of factors and their states

2) The second stage, develop a BN model : (a) identification of road damage factors using questionnaire 1 and descriptive statistical analysis ; (b) determine relationship among factors using questionnaire 2 ; (c) compute CPTs from secondary data and questionnaire 3 (d) develop a BN model using software genie 2.0
3) The third stage, model validation



Fig 3. Method to develop BN

## **RESULTS AND DISCUSSION**

## A. Variable and Category

To create a Bayesian network, the first step is determine the variables and categories (state) that affect the prediction of the condition of the pavement. The variables in this study consisted of dependent and independent variables. The dependent variable (dependent) is the condition of the pavement which is represented by the value ofInternational RoughnessIndex (IRI) and Surface Distress Index (SDI). The value of IRI and SDI is the measuring parameter in the functional condition of the road surface based on the method of Highways. The independent variable in this study was determined by filtering from the results of the literature study and preliminary survey by questionnaire with the experienced experts. The determination of the independent variable form factors that cause damage to the road from the literature study results are summarized in Table 1 below.

Table 1 Independent Variable from literature study

No	Independent Variable
1	Maintenance
2	Heavy vehicle
3	Air temperature
4	Rainfall
5	Drainage Systems
6	Implementation quality of Work

Source : Literature Study

Respondends in this research were expert profesional for roads with experience for more than 10 years. To determine the variables affecting road conditions, preliminary questionnaire were spread to 8 experts consisting of road expertise in the surrounding area of BBPJN V, consultants and road expertise professional. Results of the questionnaire are stated in table 2 is as such.

Table 2 Variables affected by road conditions

No	Factors /Variables		]	Res	po	nd	ent	s		Min	Max	Maan	Std	Pople
INU	ractors/ variables	1	2	3	4	5	6	7	8	IVIIII	IVIAX	Wiean	Dev	Kalik
1	Road maintenance	5	5	4	2	5	4	5	5	2	5	4.38	1.061	3
2	Traffic loading	4	5	5	5	5	5	4	5	4	5	4.75	0.463	2
3	Temperatures	3	3	3	3	4	4	3	4	3	4	3.38	0.518	5
4	Rainfall	3	4	3	1	4	3	3	5	1	5	3.25	1.165	6
5	Drainage Systems	5	5	5	4	5	5	5	5	4	5	4.88	0.354	1
6	Implementation quality of work	4	3	4	3	5	4	5	3	3	5	3.88	0.835	4

Source : Results from processed

Of the six variables, three variables: drainage system, traffic load and maintenance of roads has an average value / mean more than 4 and very influential on road pavement damage. Other variables namely variable of temperature, rainfall and implementation quality of work have a mean value less than 3.5 that the three variables are not used in the next stage.

# B. Category

Category or determination of state of each variables obtained by interviews with experts. Category for each variable is as such:

Table 3 Category/ State variable

No	Variable	State
Α	Dependent variable	
1	International Roughness Index (IRI) andSurface Distress Index (SDI)	<ul> <li>Good</li> <li>Moderate</li> <li>Bad</li> <li>Very Bad</li> </ul>
В	Independent variable	
1	Drainage system	<ul><li>Good</li><li>Bad</li></ul>
2	Traffic Load	<ul><li>High</li><li>Low</li></ul>

No	Variable		State
3	Road maintenance	•	Comformed
		•	Inappropriate
1// 11			

## C. CONCEPTUAL BN MODEL

The next step is to make the structure of bayesian network or causal network which is the relationship of cause and effect between variables either direct or indirect. Tool used to make this cause and effect relationship among variables is by using questionnaires in the form of matrix of relationship of variables attached to road expertise. This matrix method was used to picture the relationship between parent variable to child variable.

Maintenance				
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Drainage System			TOP)	þ
Road Condition	÷	÷	÷	
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Fig 4. Relationship Matrix

Making of BN was made by ensuring that factors affecting road damage, namely the presence of road maintenance activities, traffic load, and drainage system have been taken into considerations collectively.

Based on Figure 4, it is known that all of the variables are connected directly with road conditions. Probability value/ CPT from each variables are prior probabilities because they are the parent variable. Whereas road condition variable is the node child that the probability value will be sought further.

Figure of Bayesian Network structure for condition prediction model is as such:



Fig 5. Bayesian Network Model

## **D.** Conditional Probability

According to the availability of data, the CPTs are combined from expert knowledge and road database. Road practitioners are able to provide their estimation about relative percentages of each variables.

1. CPT Initial Road Condition

The value of initial road condition based on road condition data on 2014. The state good indicate that the condition on 2014 have a good condition (IRI <4 and SDI<50) with value 5.26 Km. The state moderate indicate that the road condition have a moderate condition (4 < IRI <8 and SDI 50-100) with value 8 Km, bad condition (8 < IRI < 12 and SDI 100-150) with value 0.9 Km and very bad condition (IRI>12 and SDI >150) with value 0 Km



Fig 6. CPT Initial Road Condition

2. CPT Road maintenance

There are two states on this variable namely conformed and inappropriate. Every year there is always a road maintenance activity, but due to limited budget, not all roads are maintained in accordance with the conditions. Parameters of percentage of road maintenance if proper treatment program / according to the value of the condition and maintenance parameters are not appropriate if the handling program is not proper / in accordance with the value of the condition.





3. CPT Traffic Load

There are two states on this variable namely high traffic load and low. High traffic load in question can be ESAL value of truck of 2 axles, truck of 3 axles, trailer, semi trailer and low traffic load can be ESAL value of minibus, pick up, truck.



### 4. CPT Drainage System

There are two states on this variable namely good conditions and bad conditions. Drainage system enters into the good criteria if the road is equipped with a side channel and the channel is not clogged and is not a lot of waste that can disrupt the smooth water. The drainage system enters into bad criteria if there are no side channels and the flow of water in the system or drainage channels do not flow and there is a lot of rubbish that water flow in the drainage system becomes impaired and cannot flow properly. CPT value obtained from the processed data from P2JN and according to Public Works Minister PubblicationNo 018/T/BNKT/1990 PU Bina Marga



5. CPT Road Condition Prediction

For the calculation of probability of road condition in year t obtained from the joint probability of the initial road condition node, road maintenance, traffic load and the drainage system

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Þ	Baik	0.58	0.55	0.47	0.4	0.62	0.6	0.5	0.4
	Sedang	0.38	0.41	0.47	0.53	0.36	0.37	0.46	0.4
	RusakRingan	0.03	0.03	0.04	0.05	0.02	0.03	0.03	0.0
	RusakBerat	0.01	0.01	0.02	0.02	0	0	0.01	0.0

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Fig 11. CPT Road condition prediction

## PREDICTION RESULT

After complete the charging of CPT value of each variable, then complete DAG can be displayed with a probability value of each variable represented in the form of a bar chart. Diagram is used as the basis for calculating the probability or prediction of condition.

The road condition prediction in the next year under many factors were generated using Software Genie 2.0. The BN model is supported by Genie, which actually runs the inference algorithm for the condition prediction.

The prediction results showed that the road condition in next year is 51% in a good condition, 44% in a moderate condition, 3% in bad condition and only 1% in a very bad condition. Value road conditions increased by 14% compared to the previous condition this could be due to the maintenance of appropriate measures and quality execution of work in accordance with the standard.



Fig 12.Road Condition Probability BN has the ability to do the updating. To demonstrate the Bayesian updating ability, some scenarios have been built to demonstrate it. 1. First scenario, set evidence node maintenance

If found evidence of maintenance activities carried out in accordance with the value of the condition, then the value of the good condition of the road for the next year will increase from 37% to 59%.



Fig 13.Evidence maintenance Second scenario, set evidence drainage system

2. Second scenario, set evidence drainage system If found evidence that good drainage system and drain water functioning well, the value of the condition of the road for the next year will increase from 37% to 54 %.



Fig 14. Evidence system drainage

3. Third scenario, set evidence traffic load If found evidence that traffic load high, the value of the condition for the next year will increase from 37 % to 56%.



## CONCLUSIONS

Based on the results of this study the following conclusions are drawn :

- 1. The variables that very significant on road pavement damage is drainage system, traffic load, and maintenance of roads. The variables has an average value / mean more than 4.
- 2. From the second questionnaire using correlation matrix shows that all of the variables are connected directly with road conditions.
- 3. The prediction results showed that the road condition in next year is 51 % in a good condition, 44 % in a moderate condition, 3 % in bad condition and only 1 % in a very bad condition. Value road conditions increased by 14 % compared to the previous condition.
- 4. Fourth scenarios have been conducted to show the Bayesian updating ability. Variables that most affect the road condition prediction are maintenance variable that shown in the first scenario with a probability value 59 %, increase 29 % from previous year.

5. Method of Bayesian network can be used to predict the uncertainty and can be updated whenever there is new information. The model has the ability to consider multiple deterioration factors jointly.

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