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Development of Pavement Deterioration Models Using Markov Chain Process

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Abstract

A common phenomenon in developing countries is that the function of the pavement in the road network will experience structural damage before the completion of life is reached, and the uncertainty of pavement damage is difficult to predict. Planning for maintenance treatment depends on the accuracy of predicting future pavement performance and observing current conditions. This study aims to apply the Markovian probability operational research process to develop a decision support system predicting future pavement conditions. Furthermore, it determines policies and effectiveness in managing and maintaining roads. A standard approach that can be used by observing the history of pavement damage from year to year is to estimate the transition probability as a Markovian-based performance prediction model. The results show that the application of the model is quite optimal, changes in pavement conditions after repair can be easily compared with an increase in good condition, reaching 92.8%. Routinely and consistently handling road deterioration will give favorable results regarding pavement condition value. This will ease in the management of the road network and the accomplishment of the optimal maintenance and repair policies.

Keywords: Markov Chain; Probabilistic Process; Pavement Management; Road Maintenance.

1. Introduction

A common phenomenon in developing countries is the presence of excessive loads resulting in structural damage to the pavement before the design life is reached [1]. Repeated conditions result in significant damage that alters service life and the environment. The financing of continual overloads is a direct factor in the increase in maintenance costs [2]. The maintenance costs required for this condition are not only for grazing the function of the top pavement layer but also must consider the sub-base layer [3]. This condition is often a problem in almost every big city in Indonesia. A lack of serious attention to minor damage turns it severe [4]. The road network is a crucial land transportation infrastructure, especially for the sustainable distribution of goods and services [5]. Transportation intentionally moves goods and services from one place to another [6]. The existence of an excellent level of road service facilitates the movement of people and goods. Therefore, road damage can affect economic activity, quality of life, and the environment in an area [7].

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Optimization in road maintenance is required to obtain a proper pavement condition even with limited funds using a knowledge-based planning strategy [8]. Well-maintained roads are essential to supporting the continuity of economic and social activities [9]. The road pavement management system continues to develop with limited costs, but users are increasingly demanding to ensure good quality, safety, and comfort in driving [10]. An essential part of the system is excellent and sustainable planning and rehabilitation. It is assumed in planning that all relevant parameters are known with certainty [11]. However, its implementation is uncertain [12]. The common condition in the road pavement management system is maintaining the best road performance while maintaining the lowest possible maintenance costs. After the road is opened, road performance will decrease over time, influenced by traffic and environmental loading [13]. The damage that occurs varies with various types of conditions. It is essential to maintain optimal conditions within the time limit of maintenance. Maintenance costs will automatically increase to repair further damage if not implemented [14, 15]. However, in most cases, it will be handled after a complaint. This activity causes inefficient and unprogrammed maintenance activities, which impact waste. Model development is significant in optimizing road maintenance [16, 17].

The Markov chain model predicts pavement deterioration by incorporating pavement improvements resulting from implemented maintenance and rehabilitation measures. This model aims to enhance the prediction of infrastructure system deterioration using a Markov Chain model [18]. It bases the estimation of the deterioration process on an empirical assessment of conditions at an early stage, which road maintenance planning uses to address maintenance issues within budgetary constraints. Procedures for making optimal maintenance decisions for deteriorated systems were developed, and methodologies are developed to ensure that pavements meet specific performance criteria while minimizing expected maintenance costs [19].

Based on the literature search to present, the Markov process approach is still used as a predictive model of road performance to optimize road maintenance management with limited costs, which still meets the minimum road service standards applicable in Indonesia. Due to the total length of roads in Indonesia of 532,817 km and with the limited condition of human resources in the field of technology sector, especially in forecasting and optimizing road pavement management, the selection of models using the Markov chain application is easier to understand and apply [20].

2. Material and Methods

2.1. Study Area

The available road conditions are the primary factor in identifying road defects. While IRI, capacity, and network serve as the primary data, it's also crucial to consider other field-based condition data as well. The routine collection of pavement condition data is a subject of study. IIRMS is the primary source of pavement condition data. This data is a historical record of road conditions, road performance, and other important information, including roughness, crack, rut, potholes, AADT, and ESAL. This case study uses national road network data in West Java. The research focuses on 34 West Java national roads, as shown in Figure 1.

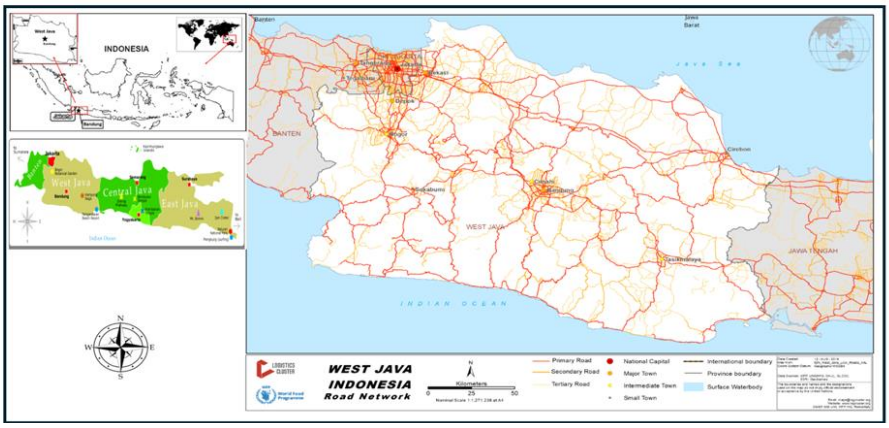


Figure 1. West Java National Road map

2.2. Data Collection

International Roughness Index (IRI) is a parameter to determine the road surface's unevenness level. It is on a scale that describes the driver’s perception of the unevenness of the pavement surface as a function of the longitudinal and transverse sections of the road surface [21, 22]. In addition, it is also influenced by vehicle operational parameters, including wheel suspension, vehicle type, vehicle height position, and speed [23]. In general, it can be defined as the deviation of the road surface as measured from level ground, plus other parameters that can affect the following: dynamic vehicle movement, quality of travel, dynamic load of construction, and water flow on the surface [24]. It is measured by scale against the road surface when vehicles move on it and is used in developing countries such as Indonesia [25].

Its value represents the quality of unevenness that affects vehicle response related to vehicle operating costs, ride quality, wheel load, and overall road surface conditions. Hawkeye data collection is considered effective with the use of equipment integrated into a commercial vehicle [19]. Figure 2 shows the equipment used in Hawkeye.

Figure 2. Hawkeye equipment

The Directorate General of Highways uses the International Roughness Index (IRI) parameter in determining road construction conditions as Table 1:

Table 1. Determination of road conditions and maintenance methods

Road Condition	IRI (m/km)	Maintenance methods	Stability level
Excellent	IRI average ≤ 4.0	Routine Maintenance	Good condition
Good	4.1 ≤ IRI average ≤ 8.0	Periodic Maintenance	
Poor	8.1 ≤ IRI average ≤ 12	Road Upgrade	Bad condition
Very poor	IRI average > 12	Road Upgrade	

The Hawkeye survey data is stored on the hard drive of the computer system within Hawkeye. The data is processed to get the users' intended-output. Figure 3 illustrates the use of the Hawkeye processing toolkit software in the data analysis process [19].

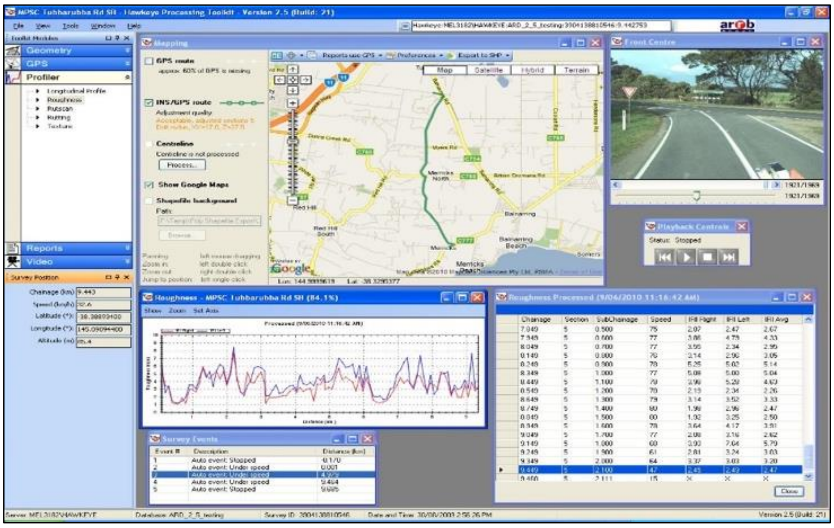


Figure 3. Hawkeye processing toolkit interface application

The data used is from the 2018–2019 period, including:

- Data on the existing road pavement condition is a variable for modeling. There are four road conditions: excellent, good, poor, and very poor.
- Road maintenance history data helps determine the type of maintenance and the amount of cost allocation performed in the previous year.

2.3. Data Analysis

The analysis phase begins with the Markov chain process [26, 27]. There are four steps:

- Determination of condition criteria.
- Calculation of the distribution of initial conditions.
- Preparation of the transition probability matrix.
- Pavement condition prediction model.

There are four condition criteria: 1) excellent, 2) good, 3) poor, and 4) very poor. State 1 represents the best condition, while state 4 represents the worst condition [28, 29]. The study used the end of 2018 as the base year (t = 0). From the road condition data for 2018–2019, the distribution of pavement conditions can be calculated based on the classification of predetermined condition values. The distribution proportion is obtained by comparing the road length under certain situations with the total under review. After getting the distribution value of the initial conditions for all states, the initial condition vector (a_0) is known [30, 31].

Furthermore, the transition probability matrix is prepared based on the transition data of road conditions in one year of pavement operation (2018–2019). The category used is handling. It means that there are actions to overcome road damage so that the value of the pavement condition can change to a better state after one cycle [32]. The types of road management programs can be in the form of routine, periodic maintenance, rehabilitation, and reconstruction [33]. The transition probability matrix organized into this category contains the increasing transition probability values [34].

The prediction application is implemented for ten years (2020–2029). The value of the prediction condition for the first year (t = 1) is included in the calculation of the second year (t = 2). Prediction of requirements for the following year is conducted similarly and is calculated until the end of the tenth year (t = 10) [18].

Figure 4 shows the flowchart of the research methodology through which the objectives of this study were achieved.

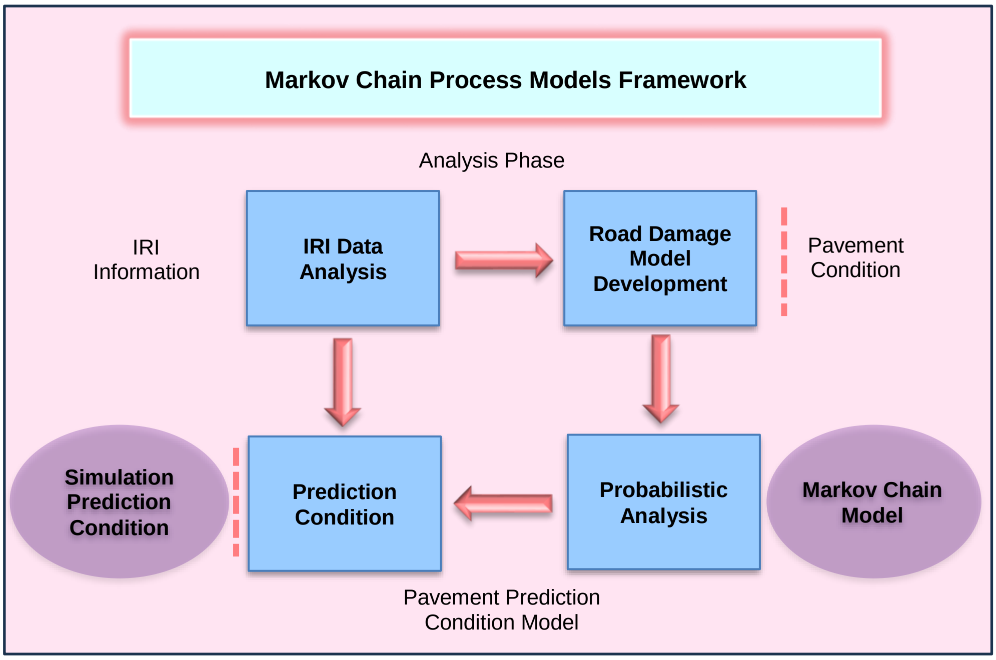


Figure 4. The framework of the development models

3. Results and Discussion

West Java Province has an area of 35,377.76 km^2 with 1,789.2 km of national roads. IRI is applicable for determining various pavement ages and speeds. A speed of 100 km/h, which is the maximum speed limit on all roadways in Indonesia, can be achieved for road surfaces with an IRI value of < 4 m/km. The following in Figure 5 is the IRI data for 2018 and 2019 used as the basis for this study. The government is having difficulty preventing it, while on the other hand, they constantly have to create prime road conditions. Markov chains are one of the best ways to model road condition performance [35]. This is because the future state of the model element is estimated only for the current state. Predicted future pavement performance depends on current conditions, not on past ones.

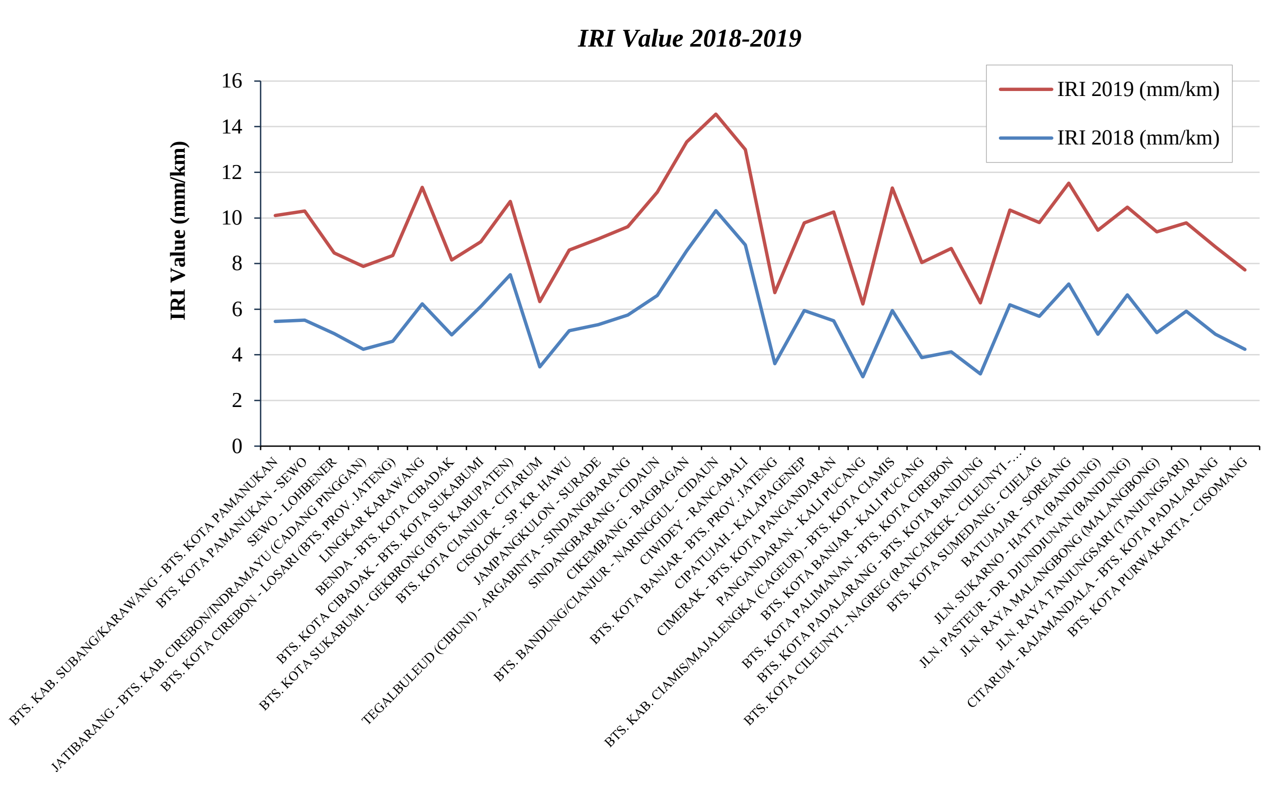


Figure 5. IRI value chart for 2018-2019

3.1. Probabilistic Analysis

The end of 2019 was used as the research base year (year 0) in this modeling using 2018-2019 data. The calculation of the distribution of pavement conditions is conducted based on the specified condition value classification. The comparison between the length of the road segment under certain conditions and the total length of the road section under review is conducted to figure out the distribution proportion. The initial condition vector will be used as the initial distribution proportion for the condition of the road section to be reviewed. The data for road conditions are provided in Table 2 based on the survey results, using 34 West Java national roads:

Table 2. The proportion of initial distribution of road conditions

No.	Road Segment Name	Initial Condition Proportion 2019			
		Good	Moderate	Light Damage	Heavy Damage
1	BTS. KAB. SUBANG/KARAWANG - BTS. KOTA PAMANUKAN	0.642	0.352	0.006	0.001
2	BTS. KOTA PAMANUKAN - SEWO	0.313	0.601	0.080	0.007
3	SEWO - LOHBENER	0.523	0.413	0.059	0.005
4	JATIBARANG - BTS. KAB. CIREBON/INDRAMAYU (CADANG PINGGAN)	0.713	0.262	0.021	0.004
5	BTS. KOTA CIREBON - LOSARI (BTS. PROV. JATENG)	0.648	0.328	0.022	0.002
6	LINGKAR KARAWANG	0.336	0.523	0.118	0.024
7	BENDA - BTS. KOTA CIBADAK	0.601	0.323	0.069	0.006
8	BTS. KOTA CIBADAK - BTS. KOTA SUKABUMI	0.610	0.388	0.003	0.000
9	BTS. KOTA SUKABUMI - GEKBRONG (BTS. KABUPATEN)	0.106	0.870	0.024	0.000
10	BTS. KOTA CIANJUR - CITARUM	0.855	0.145	0.000	0.000

No.	Road Segment Name	Initial Condition Proportion 2019			
		Good	Moderate	Light Damage	Heavy Damage
11	CISOLOK - SP. KR. HAWU	0.239	0.737	0.024	0.000
12	JAMPANGKULON - SURADE	0.372	0.605	0.023	0.000
13	TEGALBULEUD (CIBUNI) - ARGABINTA - SINDANGBARANG	0.422	0.546	0.031	0.001
14	SINDANGBARANG - CIDAUN	0.223	0.722	0.056	0.000
15	CIKEMBANG - BAGBAGAN	0.198	0.703	0.099	0.000
16	BTS. BANDUNG/CIANJUR - NARINGGUL - CIDAUN	0.016	0.952	0.031	0.000
17	CIWIDEY - RANCABALI	0.032	0.947	0.021	0.000
18	BTS. KOTA BANJAR - BTS. PROV. JATENG	0.797	0.203	0.000	0.000
19	CIPATUJAH - KALAPAGENEP	0.126	0.861	0.013	0.000
20	CIMERAK - BTS. KOTA PANGANDARAN	0.336	0.624	0.039	0.001
21	PANGANDARAN - KALI PUCANG	0.908	0.088	0.003	0.000
22	BTS. KAB. CIAMIS/MAJALENGKA (CAGEUR) - BTS. KOTA CIAMIS	0.351	0.631	0.016	0.001
23	BTS. KOTA BANJAR - KALI PUCANG	0.021	0.957	0.022	0.000
24	BTS. KOTA PALIMANAN - BTS. KOTA CIREBON	0.746	0.195	0.040	0.019
25	BTS. KOTA PADALARANG - BTS. KOTA BANDUNG	0.864	0.136	0.000	0.000
26	BTS. KOTA CILEUNYI - NAGREG (RANCAEKEK - CILEUNYI - CICALENGKA/PARAKAN MUNCANG)	0.285	0.671	0.043	0.001
27	BTS. KOTA SUMEDANG - CIJELAG	0.317	0.626	0.057	0.000
28	BATUJAJAR - SOREANG	0.119	0.832	0.049	0.000
29	JLN. SUKARNO - HATTA (BANDUNG)	0.381	0.586	0.027	0.005
30	JLN. PASTEUR - DR. DJUNDJUNAN (BANDUNG)	0.508	0.468	0.023	0.000
31	JLN. RAYA MALANGBONG (MALANGBONG)	0.545	0.416	0.039	0.000
32	JLN. RAYA TANJUNGSARI (TANJUNGSARI)	0.350	0.608	0.042	0.000
33	CITARUM - RAJAMANDALA - BTS. KOTA PADALARANG	0.598	0.396	0.006	0.000
34	BTS. KOTA PURWAKARTA - CISOMANG	0.650	0.347	0.002	0.000

3.2. Pavement Condition Transition Probability

The transition probability indicates the change in the proportion of pavement from one condition to another in one year. Furthermore, its estimation process is conducted by observing changes in each situation. The transition probability matrix for maintenance activities is found by calculating the proportion of pavement segments under certain conditions before maintenance changes to better ones afterward [36, 37]. The ratio of changes is then calculated by referring to the handling history and condition data for 2018-2019. In this study, there are four types of maintenance activities: routine, periodic, rehabilitation, and reconstruction. Each type is distinguished based on handling, work items, unit prices, and their impact on the existing pavement. The next step is calculating the transition probability matrix for each type of activity, as shown in Table 3:

Table 3. The proportion of initial distribution of road conditions

Condition	Good	Moderate	Light Damage	Heavy Damage	Total Length (km)
Good	176.938	707.752	0.000	0.000	884.690
Moderate	0.000	230.019	47.773	0.000	277.793
Light Damage	0.000	0.000	8.847	8.139	16.986
Heavy Damage	0.000	0.000	0.000	0.708	0.708
					1180.176

Next, it is compiled into a transition probability matrix by normalizing the change value for each condition, as shown in Tables 4 to 8:

Table 4. Matrix of transition probability from routine maintenance activities

Probability of Condition t Years	Probability of Condition t+1 Year			
	Good	Moderate	Light Damage	Heavy Damage
Good	0.200	0.800	0.000	0.000
Moderate	0.000	0.828	0.172	0.000
Light Damage	0.000	0.000	0.521	0.479
Heavy Damage	0.000	0.000	0.000	1.000

Table 5. The transition of conditions from periodic maintenance activities

Condition	Good	Moderate	Light Damage	Heavy Damage	Total Length (km)
Good	3,539	0.000	0.000	0.000	3.539
Moderate	6.547	46.004	0.000	0.000	52.551
Light Damage	0.000	26.541	5.308	0.000	31.849
Heavy Damage	0.000	5.308	3.362	0.354	9.024
					96.962

Table 6. Transition probability matrix of periodic maintenance activities

Probability of condition t years	Probability of Condition t+1 Year			
	Good	Moderate	Light Damage	Heavy Damage
Good	1.000	0.000	0.000	0.000
Moderate	0.125	0.875	0.000	0.000
Light Damage	0.000	0.833	0.167	0.000
Heavy Damage	0.000	0.588	0.373	0.039

Table 7. Transition of conditions from rehabilitation activities

Condition	Good	Moderate	Light Damage	Heavy Damage	Total Length (km)
Good	4.423	0.000	0.000	0.000	4.423
Moderate	38.926	33.618	0.000	0.000	72.545
Light Damage	5.308	10.262	0.000	0.000	15.571
Heavy Damage	0.354	1.239	0.000	0.000	1.592
					94.131

Table 8. Matrix probability transition from rehabilitation activities

Probability of Condition t Years	Probability of Condition t+1 Year			
	Good	Moderate	Light Damage	Heavy Damage
Good	1.000	0.000	0.000	0.000
Moderate	0.537	0.463	0.000	0.000
Light Damage	0.341	0.659	0.000	0.000
Heavy Damage	0.222	0.778	0.000	0.000

Since there is no reconstruction maintenance in the study area, the probability matrix is assumed at the start of the road construction at the beginning of the design life so that the road conditions are all in good condition, as shown in Table 9:

Table 9. Transition probability matrix of reconstruction activities

Probability of Condition t Years	Probability of Condition t+1 Year			
	Good	**Moderate**	**Light Damage**	**Heavy Damage**
Good	1.000	0.000	0.000	0.000
Moderate	1.000	0.000	0.000	0.000
Light Damage	1.000	0.000	0.000	0.000
Heavy Damage	1.000	0.000	0.000	0.000

Compilation of MPT from Markov chain modeling for model application on all roads is below:

MPT routine:

$$P = \begin{bmatrix} 0.200 & 0.800 & 0.000 & 0.000 \\ 0.000 & 0.828 & 0.172 & 0.000 \\ 0.000 & 0.000 & 0.521 & 0.479 \\ 0.000 & 0.000 & 0.000 & 0.000 \end{bmatrix} \tag{1}$$

MPT periodic:

$$P = \begin{bmatrix} 1.000 & 0.000 & 0.000 & 0.000 \\ 0.125 & 0.875 & 0.000 & 0.000 \\ 0.000 & 0.833 & 0.167 & 0.000 \\ 0.000 & 0.588 & 0.373 & 0.039 \end{bmatrix} \tag{2}$$

MPT rehabilitation:

$$P = \begin{bmatrix} 1.000 & 0.000 & 0.000 & 0.000 \\ 0.537 & 0.463 & 0.000 & 0.000 \\ 0.341 & 0.659 & 0.000 & 0.000 \\ 0.222 & 0.778 & 0.000 & 0.000 \end{bmatrix} \tag{3}$$

MPT reconstruction:

$$P = \begin{bmatrix} 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \end{bmatrix} \tag{4}$$

3.3. Pavement Condition Prediction Model with Markov Chain

Modeling is intended to determine the level of accuracy of the prediction model to the actual conditions. Furthermore, the prediction of pavement conditions is performed in the future using the MPT of each activity with the equation [38]:

$$a_t = a_0 \times P \tag{5}$$

where: a_t = Future Condition Distribution; a_0 = Initial Condition Distribution; P = MPT per type of maintenance

The type of maintenance for each segment is determined based on the proportion of lightly damaged (LD) and heavily damaged (HD) conditions by looking at the end of the previous year.

LD + HD ≤ 6% : Routine

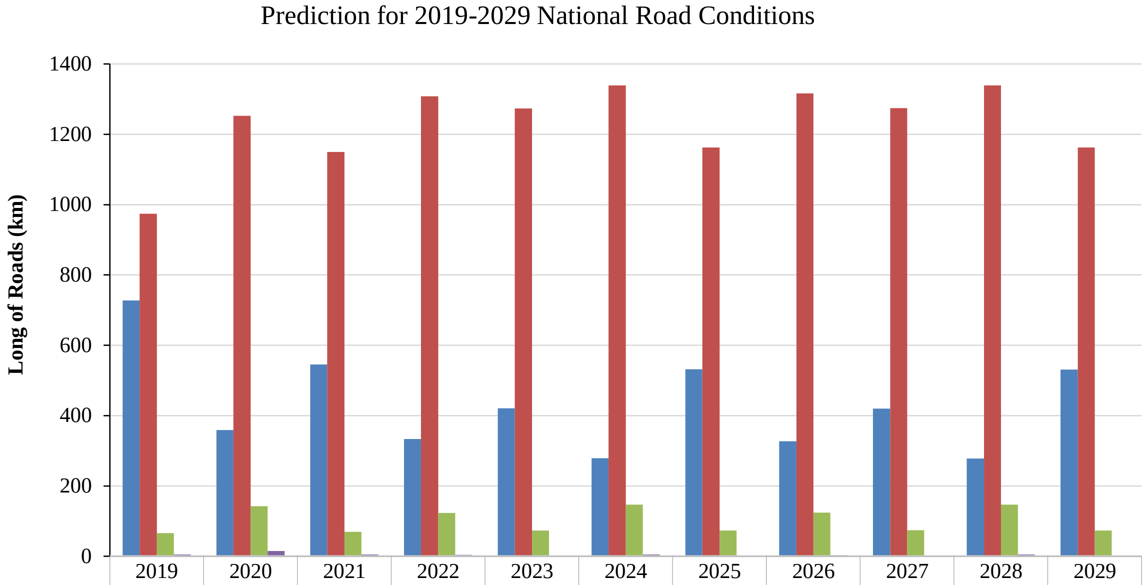
6% < LD + HD ≤ 11% : Periodic

11% < LD + HD ≤ 15% : Rehabilitation

LD + HD > 15% : Reconstruction

The following are the simulation results from the calculation of pavement conditions used to predict national road sections for the years 2019-2029.

The graph Figure 6 shows that the length of national roads in mildly damaged conditions fluctuated during the analysis year, where the most significant number was in 2028. At the same time, heavily damaged conditions were mostly found in 2020, subsequently decreasing after routine maintenance. At the end of the year of analysis, it can be seen that the results of roads in good condition are 531.23 km, moderate 1,162.48 km, lightly damaged 73.5 km, and heavily damaged 2.17 km.



	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029
Good	727.33	358.73	545.33	333.43	421.09	279.13	531.45	326.67	419.59	278.22	531.23
Moderate	973.67	1252.77	1149.33	1308.50	1273.78	1338.58	1162.46	1316.12	1274.37	1339.32	1162.48
Lightly Damaged	65.40	142.53	69.37	123.44	72.69	146.67	73.32	123.94	73.76	146.82	73.50
Severely Damaged	4.54	14.91	5.08	3.88	1.75	5.00	2.14	2.65	1.66	5.03	2.17

Figure 6. Prediction graph for 2019-2029 national road conditions

The graph in Figure 7 proves that the simulation in the road handling program for a period of ten (10) years produces a steady condition (good + moderate) of 95.72%, while the unsteady condition (light damage + heavy damage) continues to decrease to 4.28%. This indicates that the road handling program plan in this modeling is quite optimal, as it involves handling actions for all road sections on a consistent annual basis. Delaying the road handling actions, whether routine, periodic, or rehabilitation/reconstruction of road damage, will result in poor pavement condition values and incur significant handling costs.

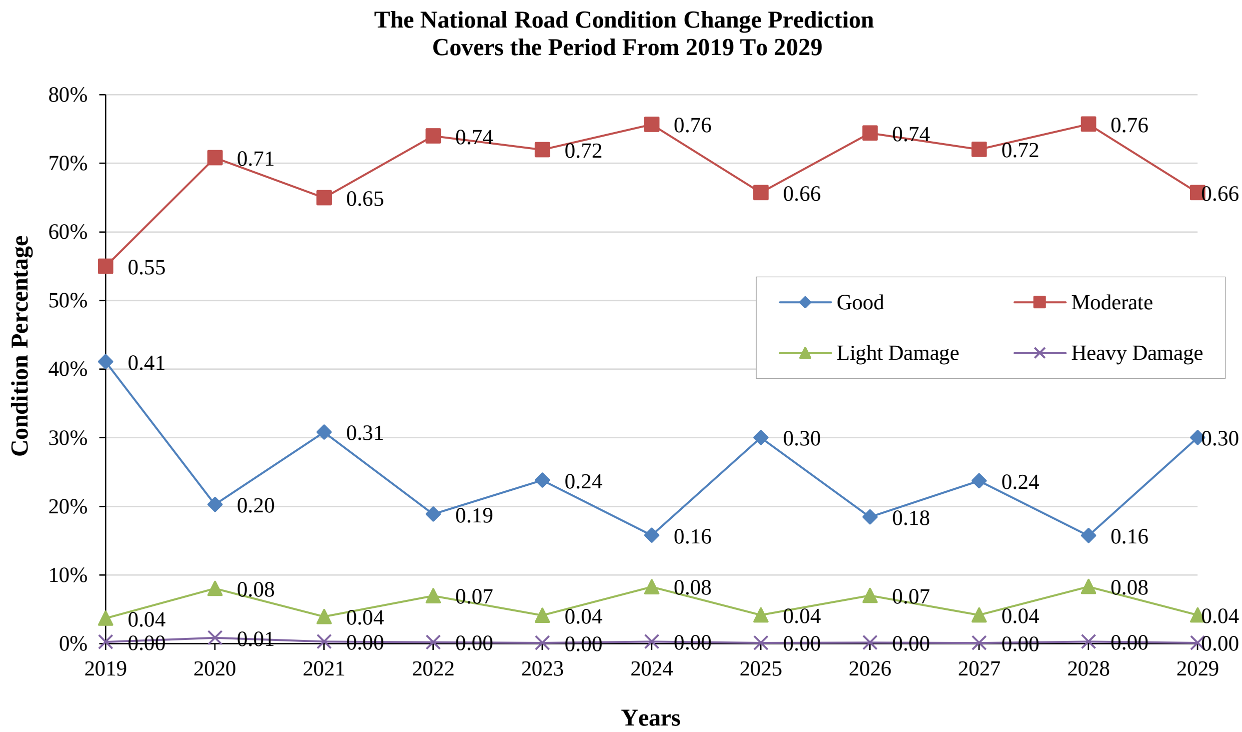


Figure 7. The National Road condition change prediction graph covers the period from 2019 to 2029

4. Conclusion

This study, conducted on 1.789,76 km of national roads across 34 locations in West Java Province, Indonesia, from 2019 to 2029, focuses on modeling the prediction of future road surface conditions to serve as a recommendation for road maintenance decision-making with a limited budget. The results demonstrated that the probabilistic Markov chain method can accurately model changes in pavement condition, leading to a good maintenance pattern that reaches 95.72% with a stable condition at the end of the design life. Routinely and consistently handling road deterioration will give favorable results in terms of pavement condition value, this will assist in the management of the road network and in making optimal maintenance and repair policies.

The model resulting from developing the Markov chain model in this study is local in the sense that its application is carried out for the study area, namely the West Java area of national roads. The use of the model for other areas outside the study area must be with specific considerations, or it can be done by making adjustments to the calculation of the initial condition vector (a_0) and MPT by the handling pattern and existing road condition data. The information from the prediction results will be beneficial to the governance of the district's road network to maintain and sustain road conditions at an acceptable level. The study found that designing a decision support system for pavement maintenance management can effectively utilize the Markov process.

5. Declarations

5.1. Author Contributions

Conceptualization, M.I., J.P., and A.I.R.; methodology, M.I., J.P., and A.I.R.; formal analysis, M.I., J.P., M.I.S., and A.I.R.; investigation, M.I. and R.K.K.; data collection, M.I. and A.I.R.; writing—original draft preparation, M.I., J.P., and R.K.K.; writing—review and editing, M.I., A.I.R., M.I.S., and R.K.K. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Acknowledgements

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5.5. Conflicts of Interest

The authors declare no conflict of interest.

6. References

[1] Rifai, A. I., Pereira, P., Hadiwardoyo, S. P., Correia, A. G., & Cortez, P. (2015). Implementation of Data Mining to Support Road Pavement Management System in Indonesia. HPJI Journal (Indonesian Road Development Association), 1(2), 93–104. doi:10.26593/.v1i2.1473.

[2] Pais, J. C., Amorim, S. I. R., & Minhoto, M. J. C. (2013). Impact of traffic overload on road pavement performance. Journal of Transportation Engineering, 139(9), 873–879. doi:10.1061/(ASCE)TE.1943-5436.0000571.

[3] Hadiwardoyo, S. P., Sumabrata, R. J., & Berawi, M. A. (2012). Tolerance Limit for Trucks with Excess Load in Transport Regulation in Indonesia. MAKARA of Technology Series, 16(1), 85–92. doi:10.7454/mst.v16i1.1336.

[4] Angreni, I. A. A., Adisasmita, S. A., Isran Ramli, M., & Hamid, S. (2018). Evaluating the road damage of flexible pavement using digital image. International Journal of Integrated Engineering, 10(2), 24–27. doi:10.30880/ijie.2018.10.02.005.

[5] Hadiwardoyo, S. P. D. (2018). Roads and Transportation Infrastructure Development Models. Quadrant, Bandung, Indonesia.

[6] Widyaningsih, N. S. H., Wan Mohtar, W. H. M., & Muhammad, I. R. (2024). Determination of Oriented Transit Development at Light Rail Transit Stations by the Process Hierarchy Analysis. International Journal on Technical and Physical Problems of Engineering, 16(58), 144–148.

[7] Ruiz, A., & Guevara, J. (2020). Sustainable decision-making in road development: Analysis of road preservation policies. Sustainability (Switzerland), 12(3), 872. doi:10.3390/su12030872.

[8] Jurkevičius, M., Puodžiukas, V., & Laurinavičius, A. (2020). Implementation of road performance calculation models used in strategic planning systems for Lithuania conditions. Baltic Journal of Road and Bridge Engineering, 15(3), 146–156. doi:10.7250/bjrbe.2020-15.489.

[9] Hankach, P., Lorino, T., & Gastineau, P. (2019). A constraint-based, efficiency optimisation approach to network-level pavement maintenance management. Structure and Infrastructure Engineering, 15(11), 1450–1467. doi:10.1080/15732479.2019.1624787.

[10] Santos, J., & Ferreira, A. (2012). Pavement design optimization considering costs and preventive interventions. Journal of Transportation Engineering, 138(7), 911–923. doi:10.1061/(ASCE)TE.1943-5436.0000390.

[11] Talib, I., Nassrullah, Z., & Abduljaleel, L. (2023). A Case Study on Reducing Traffic Congestion–Proposals to Improve Current Conditions. Civil Engineering Journal (Iran), 9(10), 2456–2466. doi:10.28991/CEJ-2023-09-10-07.

[12] Fani, A., Golroo, A., Ali Mirhassani, S., & Gandomi, A. H. (2022). Pavement maintenance and rehabilitation planning optimisation under budget and pavement deterioration uncertainty. International Journal of Pavement Engineering, 23(2), 414–424. doi:10.1080/10298436.2020.1748628.

[13] Isradi, M., Prasetijo, J., Aden, T. S., & Rifai, A. I. (2023). Relationship of present serviceability index for flexible and rigid pavement in urban road damage assessment using pavement condition index and international roughness index. E3S Web of Conferences, 429. doi:10.1051/e3sconf/202342903012.

[14] Yang, J., Lu, J. J., Gunaratne, M., & Dietrich, B. (2006). Modeling crack deterioration of flexible pavements: Comparison of recurrent Markov chains and artificial neural networks. Transportation Research Record, 1974, 18–25. doi:10.3141/1974-05.

[15] Moreira, A. V., Tinoco, J., Oliveira, J. R. M., & Santos, A. (2018). An application of Markov chains to predict the evolution of performance indicators based on pavement historical data. International Journal of Pavement Engineering, 19(10), 937–948. doi:10.1080/10298436.2016.1224412.

[16] Gao, H., & Zhang, X. (2013). A markov-based road maintenance optimization model considering user costs. Computer-Aided Civil and Infrastructure Engineering, 28(6), 451–464. doi:10.1111/mice.12009.

[17] Abaza, K. A. (2023). Simplified Markovian-based pavement management model for sustainable long-term rehabilitation planning. Road Materials and Pavement Design, 24(3), 850–865. doi:10.1080/14680629.2022.2048055.

[18] Salman, B., & Gursoy, B. (2022). Markov chain pavement deterioration prediction models for local street networks. Built Environment Project and Asset Management, 12(6), 853–870. doi:10.1108/BEPAM-09-2021-0117.

[19] Isradi, M., Prasetijo, J., Rifai, A. I., Andraiko, H., & Zhang, G. (2024). The Prediction of Road Condition Value during Maintenance Based on Markov Process. International Journal on Advanced Science, Engineering and Information Technology, 14(3), 1083–1090. doi:10.18517/ijaseit.14.3.19475.

[20] Abaza, K. A. (2017). Empirical Markovian-based models for rehabilitated pavement performance used in a life cycle analysis approach. Structure and Infrastructure Engineering, 13(5), 625–636. doi:10.1080/15732479.2016.1187180.

[21] Pérez-Acebo, H., Linares-Unamunzaga, A., Rojí, E., & Gonzalo-Orden, H. (2020). IRI performance models for flexible pavements in two-lane roads until first maintenance and/or rehabilitation work. Coatings, 10(2), 97. doi:10.3390/coatings10020097.

[22] Isradi, M., Prasetijo, J., Prasetyo, Y. D., Hartatik, N., & Rifai, A. I. (2023). Prediction of Service Life Base on Relationship Between Psi and Iri for Flexible Pavement. Proceedings on Engineering Sciences, 5(2), 267–274. doi:10.24874/PES05.02.009.

[23] [23] Siahaan, D. A., & Surbakti, M. S. (2014). Comparative Analysis of IRI Values Based on NAASRA Reading Range Variations. Proceeding The 17th FSTPT International Symposium; 22 - 24 August, 22–24.

[24] Kinasih, R. K., Prasetijo, J., Indriany, S., Isradi, M., & Biantoro, A. W. (2022). Analyzing Toll Road as a Solution to The Existing Highway Problem. Res Militaris, 12(6), 435–445.

[25] Chen, W., Zheng, M., Tian, N., Ding, X., Li, N., & Zhang, W. (2023). Project-based sustainable timing series decision-making for pavement maintenance using multi-objective optimization: An innovation in traditional solutions. Journal of Cleaner Production, 407, 137172. doi:10.1016/j.jclepro.2023.137172.

[26] Duc, N. T. T., Tai, P. D., & Buddhakulsomsiri, J. (2022). A Markovian approach to modeling a periodic order-up-to-level policy under stochastic discrete demand and lead time with lost sales. International Transactions in Operational Research, 29(2), 1132–1158. doi:10.1111/itor.13042.

[27] Sazali, A., Setiadji, B. H., & Haryadi, B. (2021). Prediction of Road Handling Cost Using Markov Chain Method in Regency Road Network. International Journal of Integrated Engineering, 13(4), 275–283. doi:10.30880/ijie.2021.13.04.026.

[28] de Oliveira, J. L. M., Davis, G., Khani, A., & Marasteanu, M. (2022). Heterogeneous Markov Chain Model to Predict Pavement Performance and Deterioration. Transportation Research Record, 2676(9), 568–581. doi:10.1177/03611981221088222.

[29] Sati, A. S., Abu Dabous, S., & Zeiada, W. (2020). Pavement Deterioration Model Using Markov Chain and International Roughness Index. IOP Conference Series: Materials Science and Engineering, 812(1). doi:10.1088/1757-899X/812/1/012012.

[30] Saha, P., Ksaibati, K., & Atadero, R. (2017). Developing Pavement Distress Deterioration Models for Pavement Management System Using Markovian Probabilistic Process. Advances in Civil Engineering, 2017, 1–9. doi:10.1155/2017/8292056.

[31] Mills, J. A., & Parent, O. (2021). Bayesian Markov Chain Monte Carlo Estimation. In Handbook of Regional Science: Second and Extended Edition: With 238 Figures and 78 Tables, 2073–2096. doi:10.1007/978-3-662-60723-7_89.

[32] Surendrakumar, K., Prashant, N., & Mayuresh, P. (2013). Application of Markovian Probabilistic Process to Develop A Decision Support System for Pavement Maintenance Management. International Journal of Scientific & Technology Research, 2(8), 295–303.

[33] Schorner, P., Tottel, L., Doll, J., & Zollner, J. M. (2019). Predictive trajectory planning in situations with hidden road users using partially observable markov decision processes. IEEE Intelligent Vehicles Symposium, Proceedings, 2019-June(Iv), 2299–2306. doi:10.1109/IVS.2019.8814022.

[34] Abaza, K. A. (2021). Empirical-Markovian approach for estimating the flexible pavement structural capacity: Caltrans method as a case study. International Journal of Transportation Science and Technology, 10(2), 156–166. doi:10.1016/j.ijtst.2020.12.007.

[35] Wang, Z., Guo, N., Wang, S., & Xu, Y. (2021). Prediction of highway asphalt pavement performance based on Markov chain and artificial neural network approach. Journal of Supercomputing, 77(2), 1354–1376. doi:10.1007/s11227-020-03329-4.

[36] Wei, B., Guo, C., & Deng, M. (2022). An Innovation of the Markov Probability Model for Predicting the Remaining Service Life of Civil Airport Rigid Pavements. Materials, 15(17), 6082. doi:10.3390/ma15176082.

[37] Vallès-Vallès, D., & Torres-Machi, C. (2023). Deterioration of Flexible Pavements Induced by Flooding: Case Study Using Stochastic Monte Carlo Simulations in Discrete-Time Markov Chains. Journal of Infrastructure Systems, 29(1), 05022009. doi:10.1061/jitse4.iseng-2109.

[38] Elsaid, F., Amador-Jimenez, L., & Mazaheri, A. (2023). Estimating Layers' Structural Coefficients for Flexible Pavements in Costa Rica Road's Network Using Full Bayesian Markov Chain Monte Carlo Approach. International Journal of Pavement Research and Technology, 16(3), 731–744. doi:10.1007/s42947-022-00160-3.