Benefits of a Maintenance Management System in Improving the Conditions of Kenyan Roads

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Abstract

A recent report on state of Kenyan roads found over 35 percent of Kenyan roads to be still in poor condition even though a comparison of the condition of the roads between 2003 and 2018 showed a successive improvement in road condition over the years. Poor road condition affects mobility and, in turn affects the country's economy. This paper develops a Machine Learning (ML) Model to assess the benefits of a Maintenance Management System (MMS) in improving the conditions of Kenyan Roadways. MMS is a computerized tool to develop the frequency of road repairs based on the level of deterioration over time in order to keep an acceptable level of service quality of the roads. We adopt a Markov Decision Process to predict the maintenance actions to be undertaken for the Kenyan road network in order to keep an acceptable level of service quality over a specified planning horizon. A budget can then be estimated based on the cost of maintenance actions. A case study using Geographic Information System maps and databases demonstrates the effectiveness of the approach.

Keywords: Maintenance Management System, Markov Decision Process, Machine Learning, Road Safety and Mobility, Kenyan Roads.

1 Introduction

Computerized Highway Maintenance Management Systems can provide an optimal maintenance policy over a specified planning horizon subject to a budget constraint. For example, such systems can offer a timeline for full repave or intermediate Maintenance Rehabilitation and Reconstruction (MR&R) for a certain highway section in order to provide a specified level-of-service. *Jha and Schultz, 2003; Jha and Abdullah, 2006; Maji and Jha, 2007*. A recent report on state of Kenyan roads found over 35 percent of Kenyan roads to be still in poor condition even though a comparison of the condition of the roads between 2003 and 2018 showed a successive improvement in road condition over the years. *Kenya Roads Board, 2018*. Figure 1 shows the GIS map of Kenyan roads and their count by surface type.

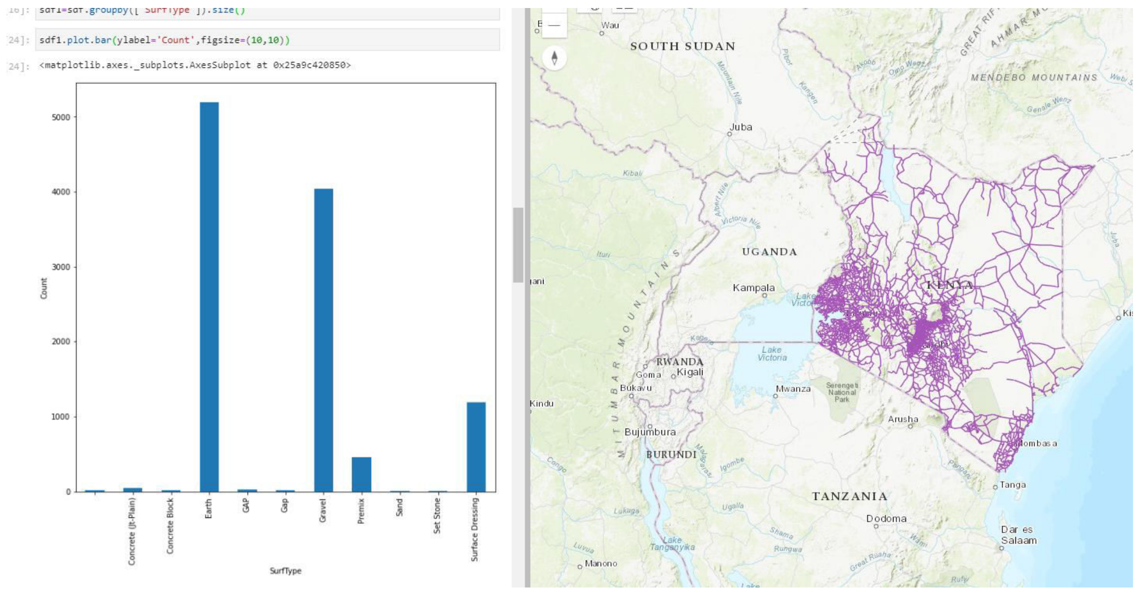

Figure 1. GIS map of Kenyan roads including their count by surface type.

It can be seen that majority of the roads are earth (that is, non-paved) roads followed by gravel roads. Only a tiny fraction of the roads are paved roads. Poor road condition affects mobility and, in turn affects the country's economy. Therefore, Kenyan roads can greatly benefit from paved roads. Furthermore, the upkeep and maintenance of paved roads is necessary in order to maintain an adequate service level.

In this paper, we adopt a Markov Decision Process to predict the maintenance actions to be undertaken for the Kenyan road network in order to keep an acceptable level of service quality over a specified planning horizon. A budget can then be estimated based on the cost of maintenance actions. A case study using Geographic Information System maps and databases demonstrates the effectiveness of the approach.

2 Methodology

Machine Learning (ML) has been extensively applied in recent years for predictive analytics, that is, to predict future conditions. For example, or research team recently applied ML to study the dynamic sight distance problem to improve traffic safety at signalized intersections with unprotected left-turns. *Jha and Ogallo, 2021.* ML, in conjunction with a Markov Decision Process (MDP) can be applied to predict the condition of roads. *Jha and Abdullah (2006).*

A Markov Decision Process (MDP) is a discrete-time stochastic control process which provides a mathematical framework for modeling decision-making where outcomes are partly random and partly under the control of the decision maker. *Wikepedia, 2021.* An MDP is a 4-tuple (S, A, P_a, R_a), where: S is a set of states called the state space; A is a set of actions called the action space; $P_a(s, s') = Pr(s_{t+1} = \alpha' | \alpha_t = s, a_t = a)$ is the probability that action a in state s at time t_i will lead to state s' at time $t+1$; $R_a(s, s')$ is the immediate reward received after transitioning from state s to state s' due to action a. A probabilistic policy function π is a mapping from state space to action space. The goal in a MDP is to find a good policy for the decision maker. To learn more about MDP readers are encouraged to refer to standard references (e.g., *Wikepedia, 2021*).

MDP has been applied for highway maintenance in our previous works. (e.g., *Maji and Jha (2007); Jha and Abdullah (2006)).* In the context of highway maintenance, a particular action, e.g., full repave, intermediate MR&R, or do nothing can be undertaken over specified time-intervals, e.g., every year, to maintain a minimum level of service. Figure 2 shows the subset of paved roads in Kenya.

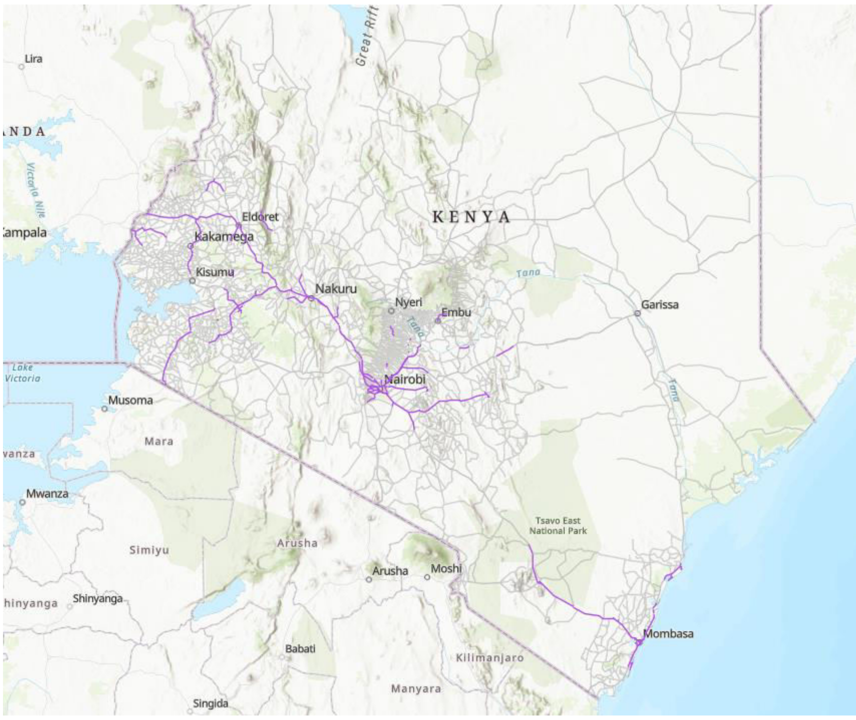

Figure 2. GIS map of paved roads in Kenya

It can be seen that paved roads are generally concentrated in Nairobi, Mombasa, Nakuru, Kakamega, Kisumu, and a few other urban areas. Table 1 below shows grouping by surface type. There are only 457 paved (or premix) roads. These roads are mainly concentrated in urban areas as shown in Figure 2.

Table 1. Grouping by surface type.

Surface Type	Total Number of Roads	Percentage
Unknown	18	0.16
Concrete (Jt-Plain)	42	0.38
Concrete Block	12	0.11
Earth	5,195	47.20
Gap	42	0.38
Gravel	4,039	36.69
Premix	457	4.15
Sand	9	0.08
Set Stone	2	0.02
Surface Dressing	1,191	10.82

An MDP can be applied to improve the conditions of the roads in Table 1. We can aggregate the roads in two broad categories: paved and unpaved, and get their condition from Table 3 of the document titled "State of our Roads, 2018" (*Kenya Roads Board, 2018*), with some averaging across the counties and some approximation.

Table 2. Percent of roads by surface condition.

Length (km) and Condition percentage	Paved	Unpaved
Length (km)	16,989.16	144,836.20
% Good	48.30	13.70
% Fair	37.88	45.75
% Poor	13.82	40.55

Source: Table 3 of *State of Our Roads, 2018* (with some averaging and approximation)

Figure 3 provides a comparative assessment of the road length and their condition. It can be seen that majority of the roads are unpaved. Also, while majority of the paved roads are in good condition, majority of the unpaved roads are in poor condition. This means there is an urgent need to improve the condition of the unpaved roads.

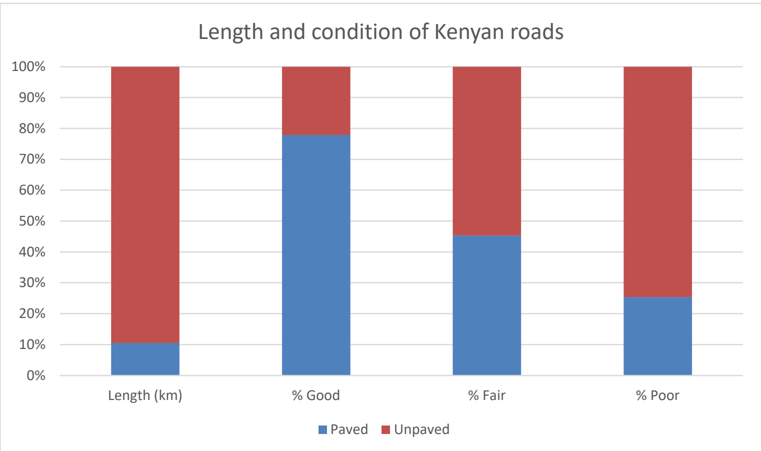

Figure 3. Length and condition of Kenyan roads.

3 Solution Approach

In order to apply the MDP, we developed a computer code in the Python language using three condition states: Good, Fair, and Poor. The screenshot below shows the condition states, transition name, and transition matrix.

```
[198]: # The statespace
       states = ["Good","Fair","Poor"]

       # Possible sequences of events
       transitionName = [["GG","GF","GP"],["FF","FG","FP"],["PP","PG","PF"]]

       # Probabilities matrix (transition matrix)
       transitionMatrix = [[0.7,0.2,0.1],[0.5,0.1,0.4],[0.1,0.1,0.8]]
```

Figure 4. Condition State, Transition Name, and Transition Matrix

Transition Name GG means the current condition of a road being Good and its condition next year being the same, that is, Good. Likewise, GF, and GF mean Good to Fair and Good to Poor, respectively. The probabilities of these transitions are shown in the transition matrix, which is 0.7, 0.2, and 0.1, respectively. The transition probabilities for Fair to Fair (FF), Fair to Good (FG), and Fair to Poor (FP), are 0.5, 0.2, and 0.1, respectively. The transition probabilities for Poor to Poor (PP), Poor to Good (PG), and Poor to Fair (PF) are 0.1, 0.1, 0.8, respectively. Other probabilities can be assumed as desired based on plans to repave or undertaking MR&R activities.

4 Results

We ran a number of scenarios to calculate the condition of a road over the next 10 years assuming its current condition to be either in Good, Fair, or Poor condition. We iterated the procedure 10,000 times to improve the reliability of the results. The 10-year condition forecast for a particular road whose current condition could be in Good, Fair, or Poor condition is shown in Figure 5.

```
The probability of starting at state:'Good' and ending at state:'Poor'= 24.87%
Condition Forecast for the next 10 years: ['Good', 'Good', 'Good', 'Good', 'Poor', 'Fair', 'Fair', 'Poor', 'Fair', 'Poor', 'Fair']

The probability of starting at state:'Fair' and ending at state:'Poor'= 25.230000000000004%
Condition Forecast for the next 10 years: ['Fair', 'Poor', 'Fair', 'Poor', 'Fair', 'Good', 'Good', 'Good', 'Good', 'Fair', 'Poor']

The probability of starting at state:'Poor' and ending at state:'Poor'= 25.05%
Condition Forecast for the next 10 years: ['Poor', 'Fair', 'Poor', 'Fair', 'Fair', 'Fair', 'Fair', 'Fair', 'Good', 'Good', 'Fair']
```

Figure 5. 10-year condition forecast of a particular roadway

It can be seen that the probability that a road will end up in a Poor condition after 10 years irrespective of its condition in the current year is fairly low (about 25%). This is because, the underlying assumption is that we are going to take intermediate actions, such as full repave or MR&R to keep the roadway condition at an acceptable level of service over successive years. The condition forecast over 10 years is also provided in Figure 5. The road whose current condition is Good remains in Good condition for next several years after which its condition drops to Poor condition. After that its condition is brought back to Fair condition by taking some MR&R action. After several years, its condition drops to Poor again. The other two set of results can be interpreted accordingly.

The result presented here can be used as a guide for condition monitoring and budget allocation. Please note that the results obtained here are based on user-specified values and random number generation, which can be replaced with actual values in real-world projects. For example, traffic volume and percentage of heavy vehicles can be used to estimate deterioration because not all roads will deteriorate at the same rate. Some roads will deteriorate at a faster rate than others. The benefit of the MR&R approach is that an individualized assessment of each roadway can be performed, including adjustment of desired transition matrix based on the road priority and budget availability.

5 Discussion

Majority of Kenyan roads are in poor condition. Rapid paving, and upkeep and maintenance of existing paved roads is necessary to improve mobility and the country's economy. This can only be achieved if a computerized maintenance managed system is in place. The example presented here shows how efficiently road conditions can be monitored over short- or long-term planning horizons, such as 5, 10, or 20 years. The example presented here shows the capability of the model in estimating road conditions in future years in an automated way instead of performing manual field inspection. The modeling approach here has to capability of being expended for large-scale application in real-world projects.

6 Conclusions

The study presented in this research shows current state of Kenyan roads and how a ML-based approach can help automatically monitor future roadway conditions. The ML approach uses MDP, which is a well-known procedure to estimate future conditions using a transition probability matrix. The authors have a great experience using the MDP approach for estimating road conditions in the United States. The same approach can be used to monitor the condition of Kenyan roadways in a computerized fashion. The condition state of Kenyan roads can be shown on a GIS map and a dashboard app can be created for monitoring purposes.

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