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Using Machine Learning for the Development of a Maintenance Management System: Case Study of Kenya

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Abstract: A Maintenance Management System (MMS) was first developed in the 1982 for implementation in the Arizona Department of Transportation in the United States. It allows for a forecast of future maintenance activities for a road network which deteriorates over time. Successive enhancements to the original MMS have been made over the years by different researchers, including some by the first author. The primary enhancements have been in the formulation and solution algorithms. The initial solution algorithms were Linear Programming (LP) and Dynamic Programming (DP), which, in some previous works, were replaced by genetic algorithms due to their efficiency over LP and DP. In this paper, we propose a Machine Learning (ML) framework for the development of a MMS, which can be a better approach than previously developed approaches. The ML framework uses a Python-based solution methodology in conjunction with geo-spatial modeling, which appears more attractive and efficient in working directly with GIS maps and databases. With respect to application, the attention is focused on African countries using Kenya as a case study example. 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. 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. The result shows that an MMS for Kenyan roads can help forecast the maintenance activities to be undertaken over a planning horizon. For more realistic practical applications, using some of our previous works as a guide, an algorithm to decide on the level of deterioration over time can be developed in future works which could consider factors like weather, vehicle mix, and traffic load.

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

1. Introduction

Computerized Highway Maintenance Management Systems (MMSs) can provide an optimal maintenance policy over a specified planning horizon subject to a budget constraint [26, 27]. 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. [1, 3, 4, 16, 24, 25].

An MMS primarily consists of three modules, namely, an input data ingestion module, an integrated Markov Decision Process (MDP) and algorithm module for backend computation, and an output module consisting of output tables and visualizations.

Previous approaches, among others, used a Linear Programming (LP) [4], Dynamic Programming (DP) [3, 24, 25], and genetic algorithms [2, 15, 16] as possible solution approaches. A Python-based Machine Learning (ML) model can be an attractive approach due to its ability to make future predictions based on data [5] and Python's ability to integrate directly with a GIS to be able to work with GIS maps and databases of road networks and other geospatial features. A similar concept was proven for efficient decision making by the first author in integrating a genetic algorithms and GIS for highway alignment optimization [27].

Application of MMS in African countries is scarce since the technology is still catching up in those countries. This paper offers an application of MMS in African countries to improve the conditions of the roads by taking proactive maintenance activities over time. A case study from Kenya is presented. We adopt a MDP 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. The data used for the study are from Kenya Roads Board: State of Our Roads 2018 (2018) [23] and from an ESRI GIS map of Kenyan roads available on the internet. Therefore, the data does not include roads that were recently paved.

2. Literature Review

Golabi et al. [4] initially developed an MMS using an MDP and LP as a solution algorithm. That MMS was tested for the Arizona Department of Transportation and showed very good results in forecasting maintenance activities over a planning horizon based on levels of deterioration of the roads and budget priorities. Many methodological improvements to the MMS have been proposed over the years, including some by the first author and his research team [6-21, 26, 27]. From a highway agency's perspective who would be interested in acquiring an MMS, a very good study was done by the first author using the Maryland State Highway Administration as a case study example [22]. That study laid out a framework to work out organizational complexities, including trade-offs preferences in the acquisition of a Computer-Off-The-Shelf Software (COTS), such as an MMS. It also identified the need for integration with existing financial management information system (FMIS), GIS, and other systems. Another interesting study done for the Maryland State Highway Administration can be found in Stephanos and Hedfi (2002). [29].

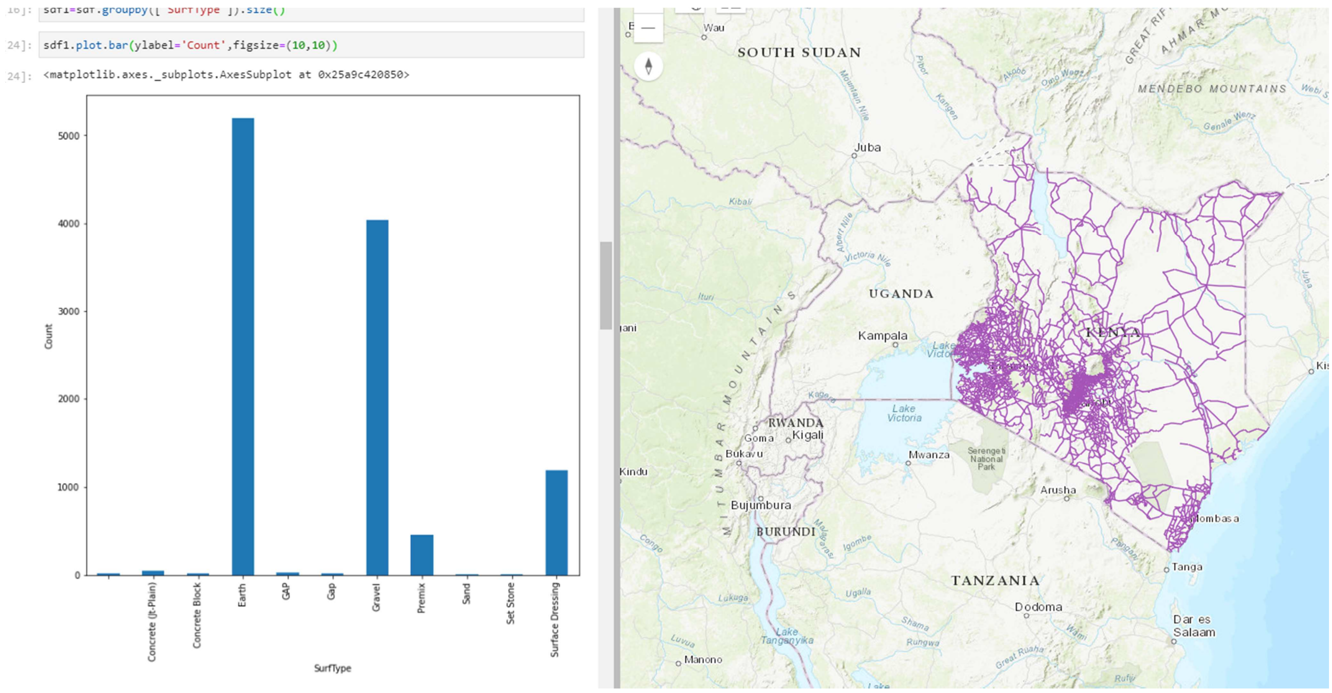

Figure 1. *GIS map of Kenyan roads including their count by surface type (Source ArcGIS mapping within our own Python framework).*

3. Methodology

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: State of Our Roads 2018 (2018) [23]). Figure 1 shows the GIS map of Kenyan roads and 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 is paved. Poor road condition affects mobility and, in turn affects the country's economy. Therefore, Kenyan roads can greatly benefit from paving. Furthermore, the upkeep and maintenance of paved roads is necessary in order to maintain an adequate service level.

ML has been extensively applied in recent years for predictive analytics, that is, to predict future conditions. For example, the 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) [5]. ML, in conjunction with a Markov Decision Process (MDP) can be applied to predict the condition of roads.

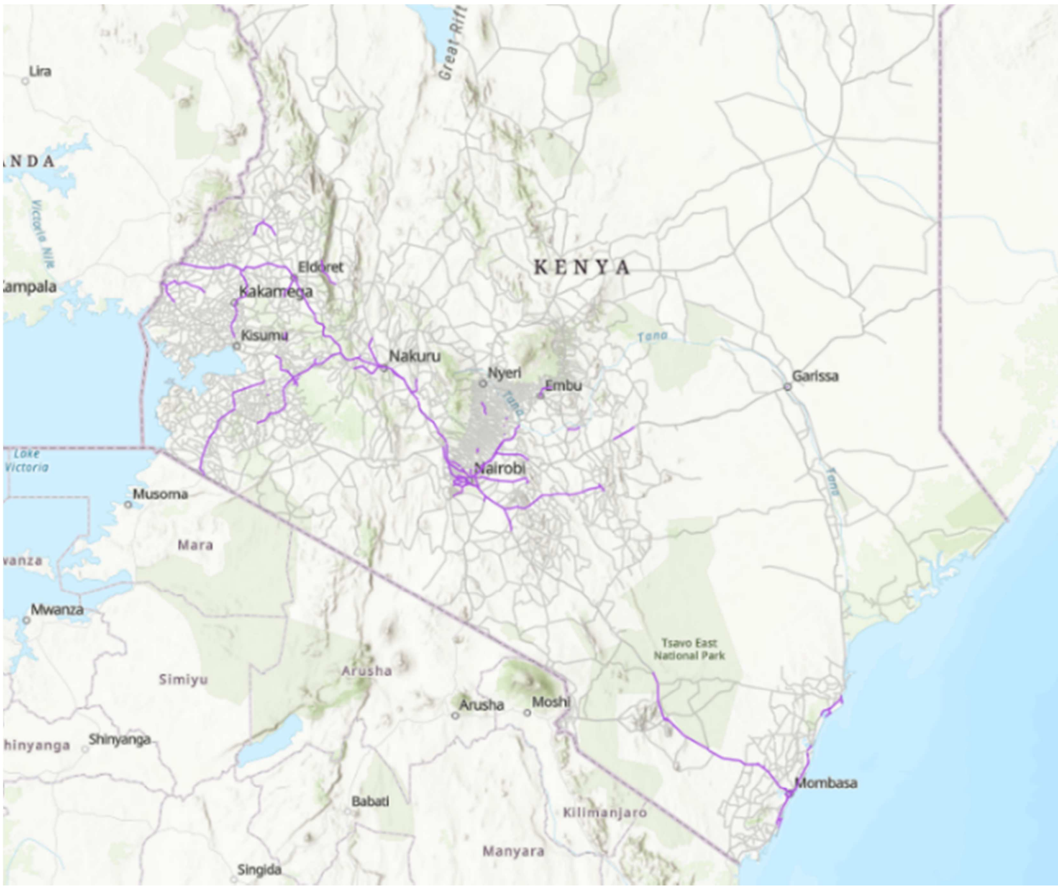

Figure 2. *GIS map of the paved roads in Kenya.*

An 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 [24-25, 29]. An MDP is a 4-tuple (finite ordered list or sequence of elements) (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) [30]).

MDP has been applied for highway maintenance in previous works. [1, 3, 18, 26]. 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.

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

Table 1. *Grouping of roads 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

Table 2 shows percent of roads by surface condition. 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 as documented in Kenya Roads Board: State of Our Roads 2018 (2018) [23] with some averaging across the counties and some approximation.

Please note that the developed method can wok irrespective of the type of paving, such as bituminous, cabro, or concrete. A further grouping of the pavements can be undertaken depending on the type of pavement and the analysis can be repeated.

Table 2. *Percent of roads by surface condition (Source: [23]).*

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

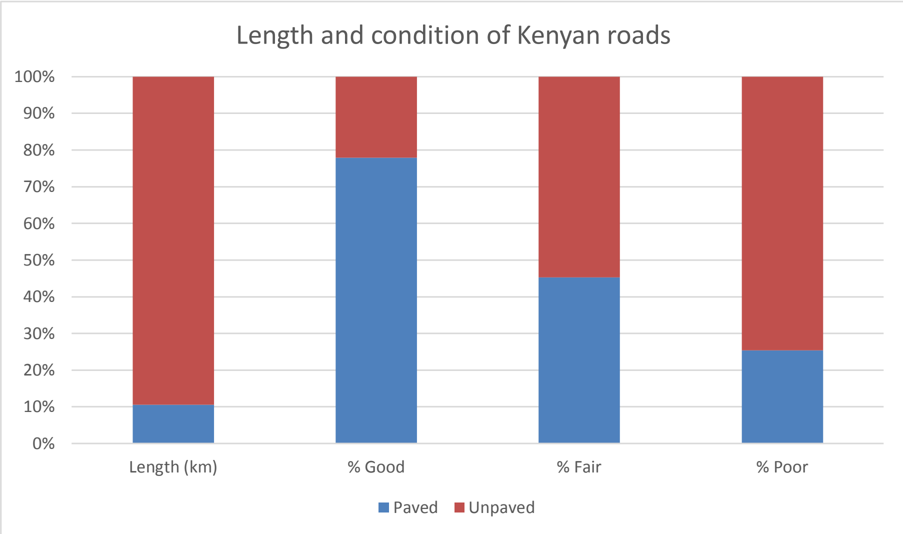

Figure 3. *Length and condition of Kenyan roads.*

Figure 3 provides a comparative assessment of the road length and their condition using the 2018 data. 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.

4. 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 Python coding interface is integrated with ArGIS. A screenshot of the Python-GIS integrated framework is shown in Figure 4.

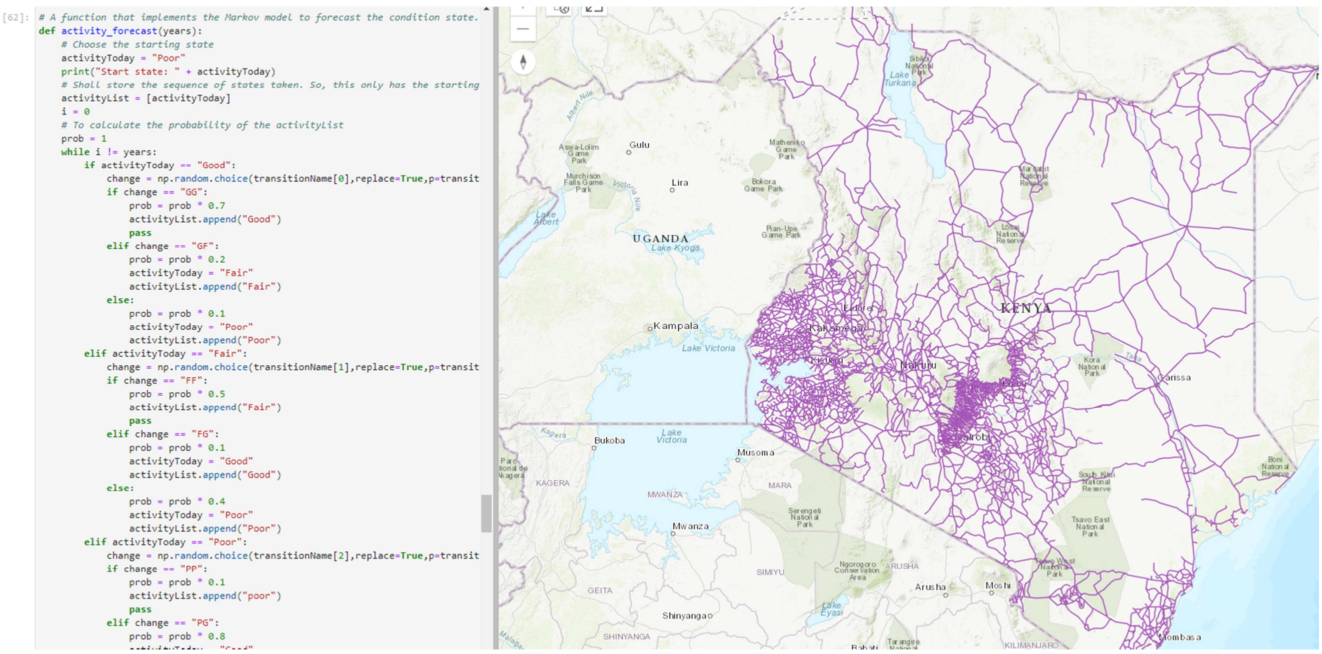

Figure 4. *Integrated Python-GIS framework.*

The screenshot in Figure 5 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 5. *Condition state, transition state, 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 of MR&R activities.

The transition probabilities can be tuned up based on historical maintenance data for a region. Alternatively, a formulation to calculate the transition probabilities based on the stochastic aspects of deterioration can be developed as suggested in our previous works [7, 9].

5. Results

A number of scenarios were executed to calculate the condition of a road over the next 10 years assuming its current condition to be either in Good, Fair, or Poor The 10-year condition forecast for a particular road whose current condition could be in Good, Fair, or Poor condition is shown in Table 3.

The possible sequence of states with a current condition of Good results in following sequence of states over the next 10 years (not counting the current year): [Good, Fair, Poor, Fair, Fair, Fair, Fair, Poor, Fair, Fair, Poor]. The possible sequence of states with a current condition of Fair results in following sequence of states over the next 10 years (not counting the current year): [Fair, Fair, Good, Good, Good, Good, Good, Good, Good, Good, Fair]. The possible sequence of states with a current condition of Poor results in following sequence of states over the next 10 years (not counting the current year): [Poor, Fair, Good, Good, Good, Good, Good, Fair, Fair, Poor, Good]. In this example, the forecast of intermediate states is based on fixed probabilities, which should change based on intermediate actions to be undertaken. For example, a Poor condition in a future year can be improved by taking appropriate MR&R action which will immediately bring the road's condition to Good in the subsequent future year. Using appropriate discount factor, a current budget can be worked out [26].

Table 3. *Results.*

Transition State	Transition Probability
GG	0.7
GF	0.2
GP	0.1
FF	0.5
FG	0.1
FP	0.4
PP	0.1
PG	0.8
PF	0.1
Start State	Good
Planning Horizon (Years)	10
Possible States	GFPFFFFPFFP
Joint Probability of the Possible Sequence of States	8.00E-06
Start State	Fair
Planning Horizon (Years)	10
Possible States	FFGGGGGGGGF
Joint Probability of the Possible Sequence of States	0.000823543
Start State	Poor
Planning Horizon (Years)	10
Possible States	PFGGGGGFFPG
Joint Probability of the Possible Sequence of States	7.68E-05

Roads experiencing heavy traffic and tucks will deteriorate at a much faster rates than those that deteriorate at a slower rate. The condition states of Good, Fair, and Poor can be analytically determined in future works based on a deterioration function using traffic load data, weather and environment conditions as well as desired MR&R action to be undertaken in intermediate years. While we have discussed these issues in some of our previous works [6, 9], case studies using real-world data remains to be done in future works.

The result presented here can be used as a guide for condition monitoring and budget allocation. 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.

6. 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 the capability of being expanded for large-scale application in real-world projects.

The application of predictive analytics using ML is a significant step which was not performed in previous works. For example, in Maji and Jha (2008) [26], we used artificial data and analytical techniques to predict maintenance priorities based on level of deterioration and budget constraint. In Jha (2010) [9], we developed mathematical techniques to understand the deterministic and stochastic process of deterioration in maintenance scheduling. In Jha, et al. (2010) [11], we used data from the Baltimore City Department of Transportation to predict maintenance activities using a genetic algorithm.

The ML framework developed in this paper cuts down the mathematical and computational complexities discussed in our earlier works. Therefore, it should be the preferred alternative.

7. 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 wide experience in the application of 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. Future works may include sophisticated formulation for deterioration calculation for each road segment using historical traffic and weather data. Future work may also involve estimating a realistic budget to ensure acceptable level of service along the roads by taking timely MR&R actions.

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