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Machine Learning Applications for Roadway Pavement Deterioration Modeling

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Abstract: Roadway and highway agencies across the globe spend a sizable fraction of their annual budget for the upkeep and maintenance of roadways. Different road segments deteriorate at different rates owing to variable traffic flow along the segments. In previous works, various forms of mathematical formulations were provided for roadway maintenance and pavement deterioration modeling. Numerical solutions algorithms using linear programming, dynamic programming, and genetic algorithms were proposed. The solution algorithms, however, did not benefit from the prescriptive and predictive capabilities of machine learning (ML) algorithms (e.g., random forest classifier, support vector machine, and artificial neural networks). Furthermore, previous methods treated transition probabilities of condition states of a pavement in future years to be static. In this paper, a variable transition probability is introduced based on the deterioration rate of a pavement over time. A modified capacitated arc routing formulation is developed for a highway infrastructure management information system. Prescriptive and predictive analytics are performed using ML to analyze the road network in simulation studies and from Montgomery County, Maryland, USA. The pavement condition index (PCI) for the road network is predicted using ML algorithms. The results show a good promise for PCI prediction based on variable deterioration rate and for obtaining condition states in future years subject to varying transition probabilities.

Keywords: pavement deterioration, Capacitated Arc Routing Problem (CARP), machine learning (ML), pavement condition index (PCI), prescriptive analytics, predictive analytics

1. Introduction

Timely maintenance of roadway infrastructure, including pavements, is of utmost importance because well-maintained roadways ensure good flow of traffic and freight, resulting in an enhanced economy of a country. However, budgetary and technological limitations associated with timely inspection and maintenance of roadways often result in poor roadway condition, which affect the safety and mobility of the motoring public, freight, and logistics operations. Poor maintenance of roadways, including bridges, may result in catastrophic collapses resulting in huge economic loss.

Due to the large number of highway networks and their varying deterioration patterns over time, timely inspection that would entail appropriate maintenance rehabilitation and reconstruction (MR&R) action to be undertaken is important. Thus, action and inspection are intertwined, i.e., action to be undertaken over a planning horizon can be represented as a conditional probability depending on the inspection to be performed.

Urban transportation networks are complex in nature, which complicates their timely upkeep and maintenance to maintain an acceptable level of service [1–4]. The principles of pavement preservation can be found in the literature of Galehouse et al. [1] and Papagiannakis and Masad [5]. Islam and Buttlar [6] discussed the effect of pavement roughness on user costs.

In previous works, various forms of mathematical formulations were provided for roadway maintenance and pavement deterioration modeling [7–13]. Numerical solutions algorithms using linear programming, dynamic programming, and genetic algorithms were proposed [14–16].

The motivation of the present study stems from the lack of current methods in using machine learning (ML) for prescriptive and predictive analytics for roadway infrastructure maintenance. The currently available solution algorithms do not benefit from the prescriptive and predictive capabilities of ML algorithms (e.g., random forest (RF) classifier, support vector machine, and artificial neural networks). Artificial intelligence and deep convolutional networks have been used in recent years in many domains, including transportation, healthcare, finance, and defense (*see*, e.g., 17–20]. This gives us an opportunity to apply ML for pavement deterioration modeling and predict future condition states subject to varying transition probabilities.

Recently, Jha and Ogallo [21] proposed a ML framework for developing a roadway maintenance action plan over time. They performed a case study using data from Kenyan roadway network to calculate the condition of a road over a 10-year planning horizon. In another recent work by Ali et al. [22], ML was used for predicting the pavement condition index (PCI) using case study data from Canada. However, the model was unable to apply a generalized method for deterioration prediction. Nyirandayisabye et al. [23] used various ML algorithms for automatic pavement damage predictions. However, the study did not consider a Markov decision process (MDP) in examining the relationships between

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pavement condition in future year as a function of pavement deterioration and various actions undertaken, such as do nothing, intermediate MR&R, or full repave. MDP is widely used for predicting future condition states because of its unique ability to relate actions, states, and time [16].

Guo et al. [24] applied a deep learning model for accurate prediction and early detection of pavement structural damage. However, the study once again, like other studies, did not incorporate an MDP in the decision-making process.

In this paper, the author seeks to fill the critical gaps in the current state of knowledge related to roadway infrastructure inspection and maintenance and offer two sets of formulations, one with variable demand and one by proposing an extension of the Capacitated Arc Routing Problem (CARP) for Highway Infrastructure Maintenance and Scheduling. An overview of different variations of roadway maintenance problems is provided followed by a description of the benefits of ML models in solving such problems. Prescriptive and predictive analytics are performed using ML to analyze the road network of Montgomery County, Maryland, USA. The PCI for the road network is predicted for future years using ML algorithms.

2. Literature Review

In previous works, a MDP was proposed to formulate the roadway maintenance problem and obtain the sequence of actions to be undertaken over a planning horizon to keep the roadway condition at an acceptable level [16, 25]. However, the pavement or infrastructure deterioration was assumed to be available exogenously. Maji and Jha [26] proposed a mathematical formulation to obtain the highway infrastructure maintenance schedule with budget constraints. The method did not consider the current PCI to forecast PCI for future years. Obazee-Igbinedion et al. [27], Obazee-Igbinedion [28], and Obazee-Igbinedion and Owolabi [29] proposed a regression modeling framework for the development of pavement sustainability index using data from the Maryland State Highway Administration database and field investigation data. The method, however, did not have the ability to forecast PCI over time in the future.

While the latest work by Jha and Ogallo [21] offered a ML framework for the development of a highway maintenance management system, pavement or roadway condition was assumed to be available exogenously. On the contrary, Ali et al. [22], Nyirandayisabye et al. [23], and Guo et al. [24] provided methods for pavement conditions deterioration but did not incorporate MDP for examining the relationship between pavement actions and resulting deterioration. This papers aims to fill this void.

3. Methodology

Pavement or highway maintenance schedules, including the deterioration rate, over a planning horizon can be calculated using the MDP [21]. It can also be calculated using mathematical functions [26].

While modern approaches to inspect pavement consist of *Lidar* via aerial and satellite imagery as well as via low flying aircrafts, manual inspections are still being performed to closely monitor and inspect cracks and potholes, and other forms of deterioration in roadways overt time. For manual inspection, an arc routing problem can be formulated to perform inspection over specified highway segments with certain constraints. When constraints are imposed, such as a highway worker's ability to perform inspection within specified time constraints, the problem mimics the characteristics of a CARP.

A special class of CARP for Highway Infrastructure Maintenance Inspection and Scheduling (HIMIS) called CARP-HIMIS is formulated to perform the maintenance activities across various roadway segments in a road network. In CARP-HIMIS, a nonnegative quantity q_{ij} is associated with each roadway segment represented as an arc (v_i, v_j). An inspection crew of m personnel, each having a capacity Q of undertaking the inspection activities, must traverse all edges or arcs of the graphs and perform the required inspection, without ever exceeding Q. As in the standard vehicle routing problem, the number of maintenance crew may be given a priori or can be a decision variable.

Arc routing problems are extensively discussed in the literature of Dror [30]. The CARP was introduced by Golden and Wong [31]. Various variations of the original CARP formulation proposed by Golden and Wong [31] have emerged since 1981. Between 1973 and 1991 (*see*, [32]), several researchers proposed heuristics for the CARP based on various edge or arc portioning criteria and on tour construction methods. In previous works of Jha et al. [15], they introduced separate formulations for inspection and scheduling and proposed a genetic algorithm to solve the problems. The genetic algorithm seemed to be efficient; however, a sensitivity analysis to test the computational efficiency as the number of arcs and node grew was not performed.

3.1. The CARP-HIMIS formulation

The formulation is an extension of our previous works reported in the work of Jha et al. [15]. Let $G = (V, A)$ be a directed graph with $n+1$ nodes. Each node represents a roadway intersection, and each arc represents a roadway segment. An inspection can be performed along a roadway segment at different periods of time. CARP-HIMIS can be formulated as:

$$\min \sum_{(i,j)\in A} \sum_{k\in K} t_{ij} \cdot x_{ijk} + \sum_{t=1}^{T} \sum_{e=1}^{E} \sum_{m=1}^{M} \sum_{s=1}^{S} \alpha^t w^t_{ems}\, c(e,m,s)[1 + \min\{\gamma(P^t), 1\}] \quad (1)$$

s.t.

$$\sum_{p\in V} x_{pik} = \sum_{p\in V} x_{ipk} \forall i \in V, k \in K \quad (2)$$

$$\sum_{k\in K} y_{ijk} = 1 \forall (i,j) \in A \quad (3)$$

$$x_{ijk} \geq y_{ijk} \forall (i,j) \in A, k \in K \quad (4)$$

$$\sum_{(i,j)\in A} \left(c_{ijk} \cdot y_{ijk} + t_{ijk} \cdot x_{ijk}\right) \leq T \forall k \in K \quad (5)$$

$$M \cdot \sum_{i,j\in V_s} x_{ijk} \geq \sum_{j,p\in S} x_{jpk} \forall S \subseteq A, 0 \in V_s, k \in K \quad (6)$$

$$y_{ijk} = \{0,1\} \forall (i,j) \in A, k \in K \quad (7)$$

$$x_{ijk} \in Z^+ \forall (i,j) \in A, k \in K \quad (8)$$

$$q^m_{ij} \leq Q, \quad \forall i,j,m \quad (9)$$

$$w^t_{ems} \geq 0 \quad \forall e,m,s, \quad (10)$$

$$\sum_m \sum_s w^t_{ms} = 1 \quad \forall e,t \quad (11)$$

$$\sum_m w^1_{ems} = q^1_{es} \quad \forall e,s \quad (12)$$

$$\sum_m w^t_{e(s+1)m} = \sum_m \sum_s w^{t-1}_{ems} p_{ms(s+1)}(m) \quad \forall e, (s+1) \tag{13}$$

$$\sum_e \sum_m \sum_s \alpha^t c(e, m, s) \leq B^t \quad \forall t \tag{14}$$

$$\begin{cases} \gamma(P^t) = 1 \; if \; P^t \geq \text{tc} \\ 0 \quad otherwise \end{cases} \tag{15}$$

where

K: allowable time intervals to perform maintenance activity; *A:* set of road segments; *V:* set of road intersections; *S:* a smaller set of road segments; V_s: a smaller set of road intersections; *i,j:* intersection pairs; *k*: time interval; t_{ij}: time to travel road segment *(i,j)* without performing maintenance activity; c_{ij}: time to perform maintenance activity along road segment *(i,j)*; *M*: a dummy positive number; *T*: allowable time to perform maintenance activity; x_{ijk}: frequency of traveling road segment *(i,j)* in *k; $y_{ijk:}$* = 1 if maintenance activity is undertaken along road segment *(i,j)* in *k*, *0* otherwise; Z^+: a set of positive integer values; α^t is a factor to calculate net worth of time value *t*; w^t_{ems} is the probability that roadway segment *e* will be in a state of *s* if an activity *m* is applied in time *t*; $c(e, m, s)$ is the cost for undertaking maintenance on road segment *e* for applying action *m* which results in state *s*; t_c = allowable deterioration to maintain the required level of service.

The objective function represented in Equation (1) minimizes total travel time to inspect a network of road segments. Equation (2) ensures route continuity while Equation (3) guarantees that each road segment is inspected at least once. Equation (4) states that a road segment must be traveled at least once. Equation (5) is the limitation on time duration while Equation (6) ensures acceptable road network. Equations (7) and (8) are problem-specific constraints. Equation (9) is a constraint to impose certain level of capacity on the road segments. Equation (10) guarantees probabilities to be greater than or equal to zero. Equation (11) guarantees maximum probability to be 1. Equation (12) assumes that we start with a given roadway state or condition in the beginning of the analysis, and Equation (13) is transition to the next state in time *t* depending on the maintenance action taken in the previous year. Equation (14) ensures upper bound on budget is maintained. B^t is the allocated money for undertaking maintenance activity *t*. In Equation (15) P^t is the probability of reactive maintenance.

3.2. MDP and deterioration function

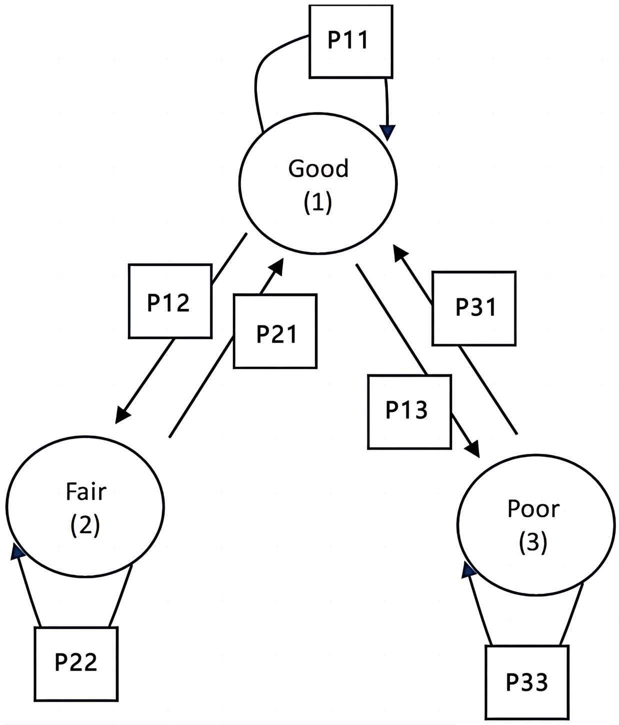
The theory of MDP is well developed and therefore has been skipped here. A schematic of three conditions state MDP applicable to roadway maintenance is shown in Figure 1. The condition states of a pavement can be either Good, Fair, or Poor determined by PCI. PCI is a number anywhere between 0 and 100. For example, a PCI above 80 can be considered to be a Good state, a PCI between 60 and 80 can be considered to be a Fair state, and a PCI below 60 can be considered to be a Poor state. The corresponding transition probabilities are shown over the arrows in Figure 1. For example, P_{11} is the transition probability of a pavement section from Good in the current timeframe to Good in the next timeframe.

The transition probability for a three condition state scenario can be represented as:

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \tag{16}$$

In previous works, transition probabilities were assumed to be exogenously available and fixed over time [21]. But, in reality,

Figure 1
MDP process for three condition states



transition probability at any time will depend on the extent of deterioration. The dynamic nature of transition probability can be addressed by first calculating the PCI_t over time *t* as follows and then calculating transition probabilities by dividing the PCI_t by 100:

$$PCI_t = \frac{t^2}{a(H_t, W_t, V_t)} \tag{17}$$

$$P_t = \frac{PCI_t}{100} \tag{18}$$

where PCI_t is the pavement condition index at *t* (usually an integer value measured as a year), *t* is time (an integer, usually a year), and *a* is a function of percent of heavy vehicles at time *t* H_t, probability of adverse weather W_t, and percent of traffic volume at peak hour V_t. Thus, *a* represents the cumulative effects of heavy vehicle percent, presence of adverse weather, and fraction of vehicles at rush hour. *Pt* is the transition probability at time *t*.

While the formulation presented in this study is developed using conditions in the United States, it is applicable in other parts of the world as long as percent of heavy vehicles probability of adverse weather percent of traffic volume at peak hour is correctly captured.

To automate the process of calculating the condition state at a specified time, a function can be defined which can be called as desired by specifying *t* and 1. An example with a *t* value of 10 and a value of 0.2 yields a condition state of Poor, as shown in Figure 2.

Three sample results for a range of *a* values for years 1, 5, and 10 are shown in Figures 3, 4, and 5.

A comparison of Figures 3, 4, and 5 shows that while condition states for the roadway segment in years 1 are Good for all *a* values, deterioration over time starts impacting its condition over time; as a result, the conditions get downgraded to Fair and Poor in future years. Please note that, as explained earlier, *a* represents the dynamic nature of deterioration.

Figure 2
Function defining the dynamic nature of pavement condition index and transition probability

```
[198]: def condition (y,a):
           pci=100-(y/a)
           p=pci/100
           if (0.8<p<=1):
               condition='Good'
           elif (0.6<=p<=0.8):
               condition='Fair'
           elif (0<=p < 0.6):
               condition='Poor'
           elif (p<0 or pci>1):
               condition='NA, Invalid Data'
           return condition

[199]: condition(10,0.2)

[199]: 'Poor'
```

Figure 3
Sample grouping of condition state for year 1

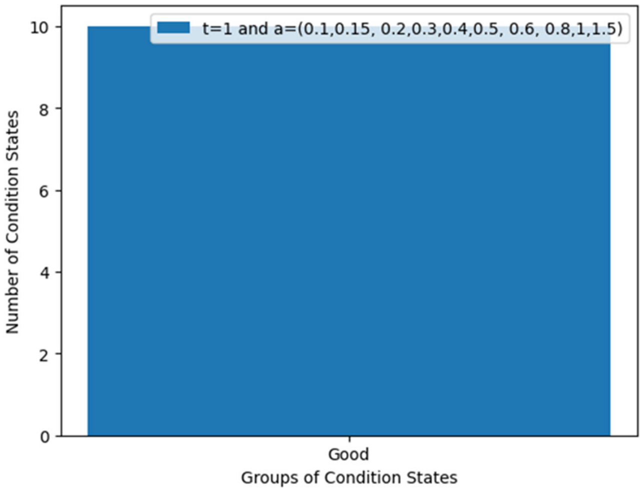


Figure 4
Sample grouping of condition state for year 5

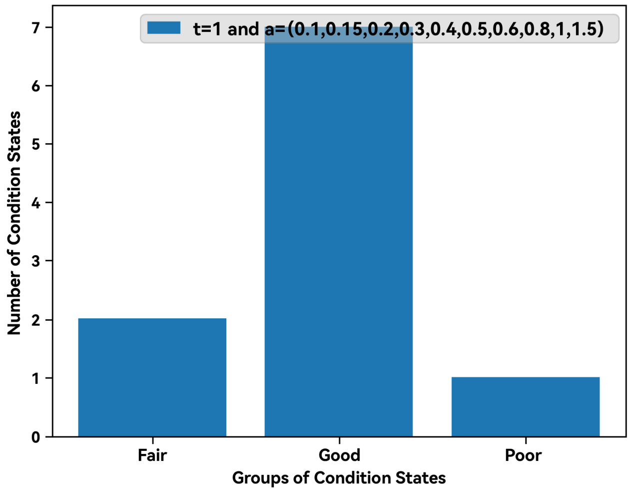
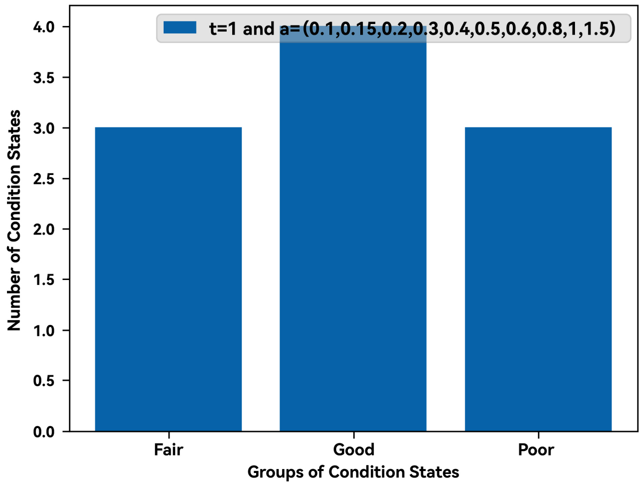


Figure 5
Sample grouping of condition state for year 10



4. Example Studies

4.1. Example 1

In the first example, we develop a ML model to decide when to undertake a maintenance action on a road segment over a planning horizon based on varying levels of deterioration. First, we test the probability of a road segment being in a Good condition after 10 years starting from a Poor condition in the current year (considered as year 0) under the transition probability shown in Equation (19).

$$P = \begin{bmatrix} 0.73 & 0.07 & 0.43 \\ 0.89 & 0.94 & 0.43 \\ 0.37 & 0.88 & 0.69 \end{bmatrix} \tag{19}$$

The conditions forecast under this scenario is found to be:

[Poor, Fair, Good, Fair, Good, Fair, Good, Fair, Good, Fair, Good].

We set up two ML models, one with a RF classifier and the other with K-nearest neighbor (KNN) classifier. We generate 10,000 random datasets on pavement condition, traffic volume, heavy vehicle percent, adverse weather percent, and percent traffic volume at peak hour. The predictor variable is whether to do nothing (0), perform some intermediate maintenance (1), or full repave (1). The code snippet is shown in Figure 6.

A test size of 0.2 and a random state of 99 are chosen. Interestingly, the RF classifier performs much better than the KNN classifier. The accuracy of RF classifier is found to be 0.985, whereas the accuracy of KNN classifier is found to be 0.565. Because the RF classifier gave us an accuracy of 0.985 for the test size and random state chosen, there was no need to perform additional sensitivity analysis. The confusion matrix for RF classifier is plotted, which is shown in Figure 7.

Figure 6
Code snippet for generating random dataset

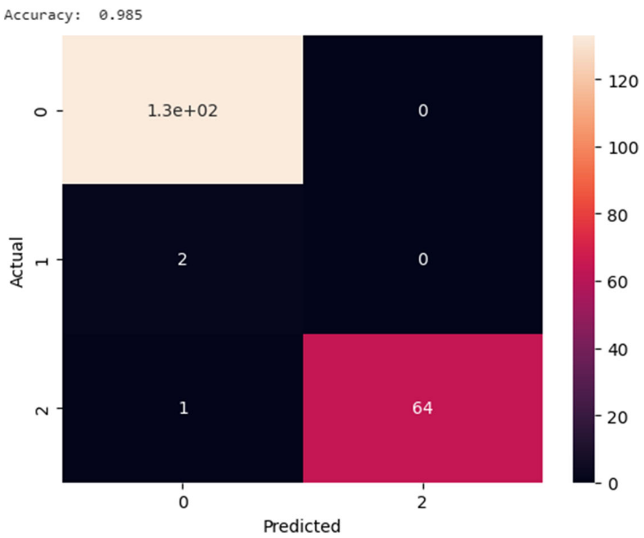
```
[32]: import math
import random
import pandas as pd
Pavement_Condition=[] # see n1 below
Traffic_Volume=[] # see n2 below
Heavy_Vehicle_Percent=[] # see n3 below
Probability_of_Adverse_Weather=[] # see n4 below
Percent_Traffic_Volume_at_Peak_Hour=[] # see n5 below
Pavement_Decision=[] # see n6 below, it can have any three integer value between 0-2
#where 0=do nothing, 1=intermediate maintenance, 2=full repave
range1=1000
for i in range(0,range1):
    n6=0
    n1=random.randint(0,2) # Pavement Condition is an Integer, 0=bad, 2=best
    n2=random.randint(10000, 65000) # Traffic volume between 10,000-65,000
    n3=random.randint(2,35) # Heavy Vehicle Percent, between 2-35%
    n4=random.randint(0,100) # Adverse weather percent, between 0-100
    n5=random.randint(10,70) #Percent Traffic Volume at Peak Hour, between 18-70
    if (n1==0):
        n6= 2
    elif (n1==1) and (n2>=40000) and (n3>=20) and (n4>=70) and (n5>=50):
        n6=2
    elif (n1==2) and (n2>=40000) and (n3>=20) and (n4>=70) and (n5>=50):
        n6=1
    elif (n1==2):
        n6=0

    Pavement_Condition.append(n1)
    Traffic_Volume.append(n2)
    Heavy_Vehicle_Percent.append(n3)
    Probability_of_Adverse_Weather.append(n4)
    Percent_Traffic_Volume_at_Peak_Hour.append(n5)
    Pavement_Decision.append(n6)

[33]: df1=pd.DataFrame([Pavement_Condition,Traffic_Volume, Heavy_Vehicle_Percent, Probability_of_Adverse_Weather,
                 Percent_Traffic_Volume_at_Peak_Hour,
                Pavement_Decision])

[34]: df2.rename(columns={0: 'Pavement_Condition', 1:'Traffic_Volume', 2:'Heavy_Vehicle_Percent', 3:'Adverse_Weather_Percent',
                     4: 'Percent_Traffic_Volume_at_Peak_Hour',5:'Pavement_Decision'}, inplace=True)
```

Figure 7
Confusion matric for RF classifier



4.2. Example 2

In this example, pavement dataset from Montgomery County, Maryland, USA is used. The summary statistics of the dataset are shown in Table 1. It shows 25,172 road segments of length ranging from 0 to 7,272.4 ft. with a mean width of about 27 inches. The mean PCI for these road segments is about 67, which means the majority of the roads segments are either in Fair or Good condition.

A histogram of PCI is shown in Figure 8.

As observed in the summary statistics table, the majority of the pavements have a PCI of 60 or above, which puts them in a Fair or Good category. However, there are pavements with PCI of below 60, which puts them in Poor category. Figure 9 shows the grouping of pavements by surface type.

Pavements labeled as AC or NOA have a PCI below 65. This means these surface types deteriorate faster than other surface types resulting in a lower PCI.

Figure 10 shows a plot of length vs. PCI. It is observed that PCI ranges from a low value to high value for shorter lengths or roads. No clear pattern is observed for road segments with longer lengths.

Figure 11 shows the roads with PCI < 20. It can be seen that majority of roads with very low PCI have a length between about 200–1,200 ft. This means mostly highly traveled roads are in Poor condition but shorter in length.

Table 2 shows the top ten streets with lowest PCI along with their length and surface type. The lowest PCI values for these streets confirm that these streets deteriorate at a much faster rate than normal because they are heavily traveled.

Figure 12(a) shows condition states, transition names, and transition matrix for the road segments with poor condition (i.e., lowest PCI). Figure 12(b) shows the possible states over an 11-year planning horizon. A high transition probability from Poor to Fair (0.8) results in the final state as Fair in the 11th year.

Figures 12(c) and 12(d) shows corresponding input and results for a high transition probability for Poor to Good (0.7). This results as an end state of Good in the 11th year.

Table 1
Summary statistics

	OBJECTID	Segment_ID	CENSUS_ID	DEPOT_NUMB	Shape_Leng	Length_1	Width	PCI
Count	25172	25172	25172	25172	25172	25172	25172	25172
Mean	12586.5	87115.69	87115.69	13.94252	480.7693	480.8341	27.33403	66.68534
Std	7266.675	39952.69	39952.69	1.907934	408.5246	408.6022	9.76293	16.60348
Min	1	32	32	11	1.125486	0	0	0
25%	6293.75	51322	51322	13	259.1789	259.175	22	56.1862
50%	12586.5	103083.5	103083.5	14	374.6538	374.7475	24	69.00005
75%	18879.25	117515.5	117515.5	15	585.6932	585.9	26	78.57
Max	25172	168228	168228	18	7272.388	7272.4	98	100

Figure 8
Histogram of pavement condition index

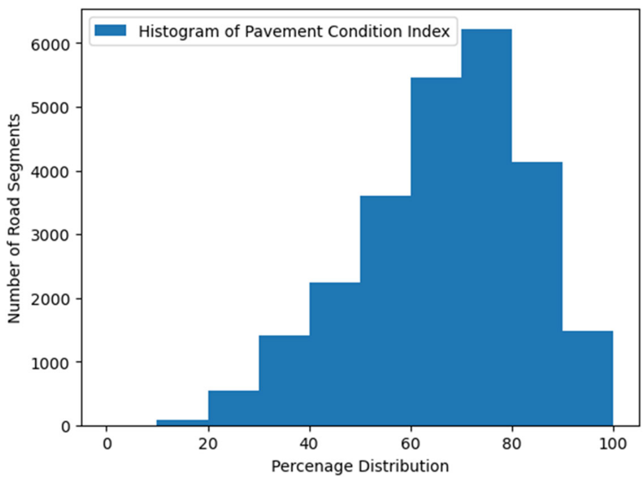


Figure 10
Length vs. PCI for road segments

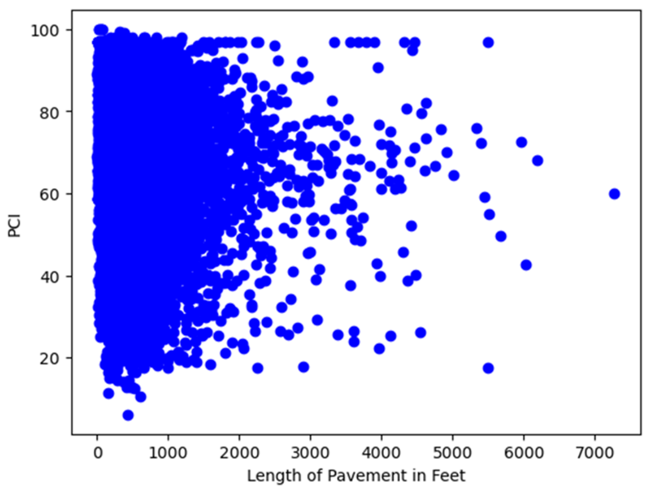


Figure 9
Grouping of pavements by surface type

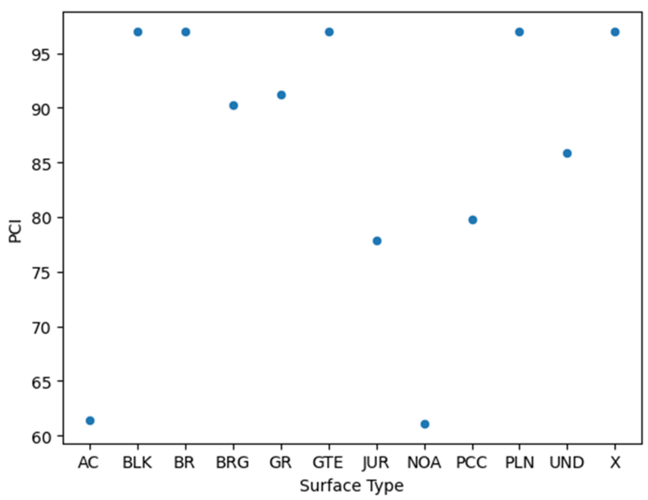
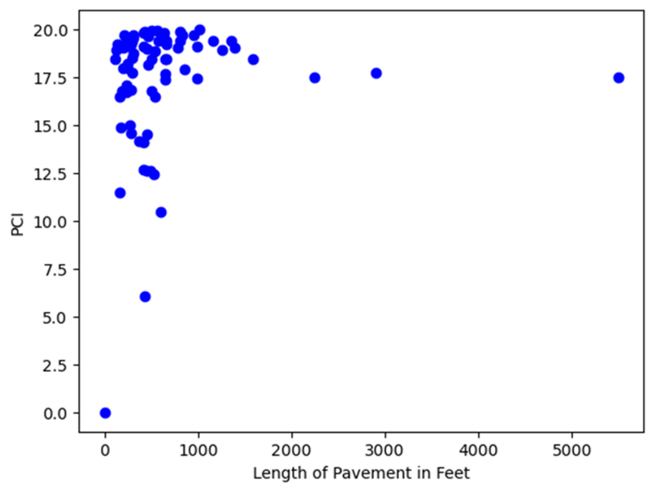


Figure 11
Length vs. PCI for road segments with PCI < 20



The simulation study presented above shows that a proactive intermediate maintenance schedule can ensure a bump in condition over successive years.

The CARP-HIMIS formulation can be applied to inspect the roads with lower PCIs of type AC and NOA on a more frequent basis as they quickly deteriorate over time. A budget forecast and

Table 2
Streets with lowest PCI

Street name	Length (feet)	Surface type	PCI
BEECH AVE	434.2	AC	6.0589
OLD DOVER RD	602.8	AC	10.4408
NORDEN DR	155.7	AC	11.4524
OLD DOVER RD	529	AC	12.4363
MAYOR LA	489	AC	12.61
TIMBER RIDGE DR	455.4	GR	12.61
VIEWPOINT CT	414.7	AC	12.6526
OLDHAM RD	420.6	AC	14.1181
DENLEY RD	363.3	AC	14.1719
RIVERSIDE AVE	450.5	AC	14.4918

Figure 12
(a) First simulation study: states, transition states, and transition matrix for the simulation study for streets with lowest PCI. (b) First simulation study: possible states over an 11-year planning horizon. (c) Second simulation study: states, transition states, and transition matrix for the simulation study for streets with lowest PCI. (d) Second simulation study: possible states over an 11-year planning horizon

(a)

```
# 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]]
```

(b)

```
Start state: Poor
Possible states: ['Poor', 'Fair', 'Poor', 'poor', 'Fair', 'Fair', 'Poor', 'Fair', 'Fair', 'Fair', 'Fair']
End state after 10 years: Fair
```

(c)

```
# 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],[0.1,0.7,0.2]]
```

(d)

```
Start state: Poor
Possible states: ['Poor', 'Fair', 'Poor', 'Good', 'Good', 'Good', 'Good', 'Poor', 'Fair', 'Poor', 'Good']
End state after 10 years: Good
```

a maintenance schedule can then be worked out using procedure developed in our previous works [26].

5. Results and Discussion

A new formulation for highway infrastructure management systems was developed by extending the concept of CARPs. The condition of road segments of Montgomery County, MD, USA was analyzed, and several simulation studies were performed to investigate the final condition state of streets with poor PCI's subject to varying transition probabilities. The results show that proactive maintenance in intermediate years may lead to a higher condition state in future years.

The formulation can be applied to find optimal allocation of budget and personnel to perform maintenance activities across various road or highway segments. The formulation can also be applied in other related problems, such as trash pickup and delivery or doing other routine activities across a road network.

The dynamic nature of the pavement deterioration over time was examined and used a dynamic transition probability over a planning horizon to more accurately obtain the PCI.

In formulating the dynamic deterioration function, the effects of a number of factors aiding to deterioration were considered, including percent of heavy vehicles at time t H_t, probability of adverse weather W_t, and percent of traffic volume at peak hour V_t.

We develop a ML model using two well-known classifiers, RF and KNN. For the dataset that we examined, RF performed better than KNN.

The prescriptive analysis using pavement data from Montgomery County, MD, USA showed a number of interesting observations were noted, which are summarized below:

- The majority of the road segments have a PCI value of 60 or above confirming that majority of the road segments are either in Fair or Good condition.
- Pavement of type AC and NOA have the lowest PCI.
- Road segments of shorter length exhibit both low and high PCI. Those with a low PCI value appear to be highly traveled.
- PCI should be calculated on a more frequent basis for road segments with low PCA values. The CARP-HIIS formulation will be particularly suitable to inspect such roads.
- A budget forecast and a maintenance schedule can then be worked out using procedure developed in our previous works.

6. Recommendations

The study revealed that: (a) CARP-HIMIS is a better way of calculating optimal maintenance and budget schedule for undertaking maintenance and pavement activities for heavily travels roads of shorter lengths; (b) in applying MDP to solving the pavement deterioration problem, transition probabilities should be considered as a variable over the planning horizon as the deterioration rate of a pavement depends on many factors, such as percent of heavy vehicles at time t H_t, probability of adverse weather W_t, and percent of traffic volume at peak hour V_t.; (c) if a large pavement dataset is available, then ML algorithms can be developed to perform the predictive analytics to make the decision of what maintenance action to undertake over the planning horizon; (d) ML can be used for performing efficient prescriptive analytics to get insight into pavement conditions of a road network, such as the relationship between PCI and road length; and PCI and surface type; and (e) condition states in future years can be analyzed subject to varying transition probabilities reflecting the intermediate maintenance activities undertaken.

The study revealed many new contributions for pavement and roadway maintenance, in general, especially using ML procedures. The methods developed here can be further expanded by analyzing additional datasets and can be applied to other jurisdictions.

6.1. Application of the model to other jurisdictions

While the case studies presented in the paper are conducted using the data from the United States, the basic concepts presented are applicable in any road network in the world. For example, the nature of road deterioration as a function of traffic load, weather, percentage of heavy vehicles, and other parameters presented in the study will generally be non-linear in nature. Also, the pavement activities are generally conducted at fixed time intervals (e.g., every 6 months or every year).

If the datasets were available from other jurisdictions around the world, the underlying empirical equations can be further calibrated for specific application of the model in those jurisdictions. For example, we did a study last year using road network data from Kenya [21]. Similar studies can be conducted for other parts of the world. The theory presented here will be equally applicable in any of those cases.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

Manoj K. Jha is an Associate Editor for *Journal of Computational and Cognitive Engineering*, and was not involved in the editorial review or the decision to publish this article. The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Manoj K. Jha: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization.

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