DEVELOPMENT AND IMPLEMENTATION OF A NETWORK-LEVEL PAVEMENT OPTIMIZATION MODEL FOR OHIO DEPARTMENT OF TRANSPORTATION

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ABSTRACT

Optimal use of pavement maintenance and rehabilitation budget is essential in a constrained budget environment such as now. This paper presents the development and implementation of a network-level optimization model within a pavement management information system (PMIS) for the Ohio Department of Transportation (ODOT). Future pavement condition is predicted based on historical pavement data using a Markov transition probability model. Such transition probabilities are updated automatically when new condition data become available each year. The network-level optimization model integrates a linear programming model and the Markov transition probability model. This optimization tool is capable of (1) calculating the minimum budget required to achieve a desired level of pavement network condition, (2) maximizing the improvements of pavement network condition with a given amount of budget, and (3) determining the corresponding optimal treatment policy and budget allocations. It can be used by highway agencies as a decision support tool for network-level pavement management decisions.
INTRODUCTION

As a result of the aging pavement networks compounded by budget cuts at most agencies, maximizing the benefits of available maintenance and rehabilitation dollars has become necessary for many highway agencies. This paper presents the development and implementation of a network-level pavement optimization model for the Ohio Department of Transportation.

The model is developed using the linear programming algorithm and the Markov transition probability model. The Markov transition probabilities are estimated based upon historical pavement condition data collected by ODOT and such probabilities can be updated automatically when new data become available. The Markov transition matrices are developed for each pavement group with similar characteristics, such as pavement type, last treatment, and system priority. A linear programming optimization model is then established based on the Markov model. The network-level optimization model is implemented using Microsoft Visual Basic .NET (2008). The objective function as well as various constraints, such as the available budget, the allowable treatments at various condition states, and the desired target condition level, can be modified to satisfy the needs of the decision maker. This optimization tool is capable of (1) calculating the minimum budget required to achieve a desired level of pavement network condition, (2) maximizing the improvements of pavement network condition with a given amount of budget, and (3) determining the corresponding optimal treatment policy and budget allocations.

LITERATURE REVIEW

Previously proposed optimization models have two essential components, which are optimization algorithms and pavement condition prediction models (1). Integer and linear programming are two optimization algorithms utilized by most developed pavement optimization models. Li et al. (2) and Ferreira et al. (3) use integer programming models, in which each pavement section is assigned a decision variable and a specific maintenance and rehabilitation plan can be generated for each pavement section. However, this approach results in a very large number of variables and makes the optimization process extremely difficult especially when it is used for large pavement networks (4). On the other hand, linear programming models can be solved within an acceptable time period even if the problem size is quite large (5). Therefore, many researchers, such as Abaza (4), Golabi et al. (6), Bako et al. (7), and Chen et al. (8), have developed network-level optimization models using linear programming. In linear programming models, decision variables are introduced for pavement condition categories instead of specific pavement sections (4). There are two main types of condition prediction models, namely probabilistic models and deterministic models. The rate of pavement deterioration is often uncertain (9). Therefore, the probabilistic model based on the Markov process is the most frequently used approach (4, 6, 7, 8).

The development of the optimization model in this research is mainly based on the methodologies adapted from the models developed by Golabi et al. (6) for Arizona DOT and by Chen et al. (8) for Oklahoma DOT. In Golabi et al.’s model, a single Markov transition probability matrix is used to estimate the deterioration trend of pavements receiving routine maintenance, no matter what type of repair treatment has been conducted (8). As a result, pavements with different repair treatments, such as reconstruction and thin overlay, are assumed to deteriorate at the same rate, which is considered by Chen et al. (8) as a major limitation of this model. The main improvement of Chen et al.’s model is that it uses two Markov transition
matrices for each repair treatment. One is for the immediate impact of the treatment on the pavement condition improvement when it is conducted. The other is for the deterioration trend after the treatment. In other words, the deterioration trends for different repair treatments are estimated separately. Therefore, this model is more realistic and accurate in that pavements with different last treatments tend to deteriorate at different rates (8).

**DEVELOPMENT OF MARKOV TRANSITION PROBABILITY MODEL**

The Markov transition probability model assumes that the probabilities that a pavement deteriorates from a given condition state to other condition states are “stationary transition probabilities” (5, 10).

In this paper, pavement conditions are categorized into five states: Excellent, Good, Fair, Poor and Very Poor, based on the pavement condition rating (PCR) score; pavement repair treatments are grouped into four types: Preventive Maintenance (PM), Thin Overlay, Minor Rehabilitation and Major Rehabilitation. The Markov transition probabilities should be estimated for each pavement group with similar characteristics. However, a pavement group must have a significant amount of pavements at various condition states to develop a reliable prediction model (10). Therefore, three critical factors, namely pavement type, system priorities and last repair treatment, are used as parameters to define pavement groups. Two transition probability matrices: the treatment matrix and the Do Nothing matrix, are developed for each repair treatment in each pavement group. The treatment matrix is for the condition improvement the first year the treatment is applied and the Do Nothing matrix is for the deterioration trend after the treatment.

There are three challenges in estimating the Markov transition matrices from actual historical data. First, “outliers” in the data need to be excluded to improve the accuracy of the estimation. An example of the outliers is that a pavement section in poor condition may become in good condition the next year without any record of repair treatment. Such pavement sections are removed from the calculation process in this research. Second, pavement condition data are often subject to “attrition”, also referred to as “dropouts” (11). Overtime, only good performing pavements remain, while poor performing pavements are more likely to receive treatments and “drop out”; therefore, prediction models that do not consider dropouts tend to overestimate future pavement conditions, particularly at the later stage of pavement life span (10). This issue is handled by projecting the PCR scores in the next 20 years for each pavement section, assuming that no repair treatment is conducted. The actual historical PCR data and the forecasted PCR data are used in estimating the transition probabilities to offset the impact of those “dropouts”. Third, some pavement groups do not have a sufficient amount of pavements, making the transition matrices less accurate and sometimes unrealistic. For this research, the total mileage of a pavement group should be at least 300 miles; otherwise, the transition probabilities are derived from other similar groups.

**FORMULATION OF NETWORK-LEVEL OPTIMIZATION MODEL**

This section presents the development of a linear programming model for network-level pavement optimization based on the Markov transition probability model.

The pavement network is divided into three sub-networks according to the pavement types (1, Concrete; 2, Flexible; 3, Composite). Each sub-network is divided into four groups according to the last repair treatments (1, PM; 2, Thin Overlay; 3, Minor Rehabilitation; 4, Major...
Rehabilitation). Each group is further divided into five pavement condition states (1, Excellent; 2, Good; 3, Fair; 4, Poor; 5, Very Poor) based on the PCR score. Each pavement condition class may be recommended for one of the five repair treatments (0, Do Nothing; 1, PM; 2, Thin Overlay; 3, Minor Rehabilitation; 4, Major Rehabilitation). In the optimization model described in this section: \( N \) is the number of pavement types, \( K \) is the number of repair treatment types, \( I \) is the number of pavement condition states and \( T \) is the number of analysis years. \( Y_{nkti} \) is the decision variable representing the proportion of pavement type \( n \) in condition state \( i \) with last treatment \( k' \) receiving recommended repair treatment \( k \) in year \( t \). Two assumptions are: the total mileage of the pavement network remains constant, and the pavement types do not change for any pavement section during the analysis period.

Two objective functions are developed. The first one is to minimize the total repair cost of the pavement network to achieve a target condition level (Equation 1):

Minimize

\[
\sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{k'=1}^{K'} \sum_{i=1}^{I} \sum_{k=0}^{K} Y_{nkti} Y_{nkti}' \cdot C_k
\]  

where \( C_k \) is the unit cost of applying treatment \( k \).

The second objective function is to maximize the proportion of pavements in Excellent, Good, and Fair condition over the analysis period with given budget constraints (Equation 2):

Maximize

\[
\sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{k'=1}^{K'} \sum_{i=1}^{I} \sum_{k=0}^{K} Y_{nkti}
\]  

There are four sets of required constraints namely non-negativity constraints, sum-to-one constraints, initial condition constraints, and state transition constraints. The non-negativity constraints (Equation 3) ensure that all variables in the optimization model are non-negative.

\[
Y_{nkti} \geq 0 \ (n = 1, \ldots, N; t = 1, \ldots, T; k' = 1, \ldots, K; i = 1, \ldots, I; k = 0, \ldots, K)
\]  

The sum-to-one constraints (Equation 4) ensure that the entire pavement network is divided into many proportions and every proportion is represented by a decision variable.

\[
\sum_{n=1}^{N} \sum_{k'=1}^{K'} \sum_{i=1}^{I} \sum_{k=0}^{K} Y_{nkti} = 1 \ (t = 1, \ldots, T)
\]  

The initial condition constraints (Equation 5) pass the values representing the current pavement network condition distribution to the optimization model.

\[
\sum_{k=0}^{K} Y_{nkti}' = Q_{nkti} \ (n = 1, \ldots, N; k' = 1, \ldots, K; i = 1, \ldots, I)
\]  

where \( Q_{nkti} \) is the proportion of pavement type \( n \) in state \( i \) with last treatment \( k' \) in initial year.
The state transition constraints (Equation 6) integrate the Markov transition probability model with the linear programming model. From the second analysis year on, the proportion of pavement type \( n \) in condition state \( j \) with last treatment \( k' \) in year \( t \) is derived from two parts of pavement in various condition states in year \( t-1 \): one part with last treatment \( k' \) receiving no new treatment (Do Nothing) and the other part receiving new treatment \( k \).

\[
\sum_{k=0}^{K} \sum_{i=0}^{N} \sum_{k'=1}^{K} Y_{nk'ik} = \sum_{i=0}^{N} \sum_{k=1}^{K} Y_{n(t-1)ik} \cdot P_{nk'ij} + \sum_{i=0}^{N} \sum_{k=1}^{K} Y_{n(t-1)i0} \cdot DN_{nk'ij}
\]

\( n = 1, \ldots, N; t = 2, \ldots, T; k' = 1, \ldots, K; j = 1, \ldots, I \) (6)

where \( P_{nk'ij} \) is the probability that pavement type \( n \) receiving new treatment \( k \) transit from state \( i \) to state \( j \) and \( DN_{nk'ij} \) is the probability that pavement type \( n \) with last treatment \( k' \) receiving no new treatment (Do Nothing) moves from state \( i \) to state \( j \).

In order to make the optimization model more practical, several sets of optional constraints are also introduced. The condition constraints (Equation 7 and 8) ensure that the proportion of pavement in certain condition states is in a prescribed range.

\[
\sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{k'=0}^{K} Y_{nk'ik} \leq \varepsilon_{it} \quad (t = 2, \ldots, T; \text{selected } i) \quad (7)
\]

\[
\sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{k'=0}^{K} Y_{nk'ik} \geq \varepsilon_{it} \quad (t = 2, \ldots, T; \text{selected } i) \quad (8)
\]

where \( \varepsilon_{it} \) is the upper limit of the proportion of pavement in condition \( i \) in year \( t \) and \( \varepsilon_{it} \) is the lower limit of the proportion of pavement in condition \( i \) in year \( t \).

For instance, pavements in Poor and Very Poor condition are considered as deficient. It may be desirable to limit the total amount of deficient pavements (or deficiency level) to a given percentage, say, 5%, of the entire network. If the desirable deficiency level is much lower than the existing deficiency level, a significant amount of rehabilitation would be required to achieve the desired condition target immediately. Therefore, it is more reasonable to allow the condition target (in term of desired deficiency level) to be achieved gradually by linearly reducing the proportion of deficient pavements using Equation 9:

\[
\varepsilon_{it} = \begin{cases} 
\varepsilon_{it} - \frac{\varepsilon_{it} - \varepsilon_{i}(t-1)}{t'-1} & 2 \leq t \leq t' \\
\varepsilon_{i} & t' < t \leq T 
\end{cases} \quad (9)
\]

where \( \varepsilon_{i} \) is the desired proportion of condition state \( i \); \( \varepsilon_{it} \) is the upper limit of proportion of pavement in condition \( i \) in year \( t \); \( t' \) is the year to achieve condition target specified by the user and \( T \) is the number of analysis years.

The allowable treatment constraints (Equation 10) ensure that certain treatments can only be applied to pavements in certain condition states or with certain last treatments.

\[
Y_{nk'ik} = 0 \quad (t = 1, \ldots, T; \text{selected } n, k', i, k) \quad (10)
\]
Experience reveals that some treatments are cost effective only when pavements are in certain condition states and with appropriate last treatments. For example, Thin Overlay is only cost effective on pavements in Fair or Poor condition, so the corresponding decision variables are set to zero to disallow Thin Overlay on pavements in other condition states.

The effectiveness of some treatments is also associated with the last treatment. For instance, if PM is conducted on pavements with last treatments of PM, the underlying distress of the pavement can only be “masked” for a short period of time and the distress may resurface quickly within a few years after treatment. However, PM is a lower cost treatment, which may cause the optimized solution to recommend PM treatments to be applied repeatedly. Therefore, it is necessary to add a set of constraints to limit the use of repeated PM treatments on certain pavements.

The budget constraints (Equation 11) ensure that the required budgets recommended by the optimized solution do not exceed the maximum available budget for each year.

\[
\sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{k=0}^{K} Y_{n,t,k,i} \cdot C_{k} \cdot L \leq B_{t} \quad (t = 1, \ldots, T)
\]

where \( L \) is the total length of the entire pavement network and \( B_{t} \) is the maximum available budget in year \( t \).

The budget constraints are required for the maximization model and optional for the minimization model. It is possible that the optimized repair policy obtained from the mathematical model would recommend a large number of pavements to be repaired in the first couple of years in order to minimize the total cost over the analysis period. However, the recommended budget may be far beyond the maximum available budget of the highway agency, making the optimized repair strategy unsuitable for practical use. For that reason, the budget constraints can also be included in the minimization model.

IMPLEMENTATION

The network-level optimization model is implemented using Microsoft Visual Basic .NET (2008). The model is solved by an open source linear programming solver, named LP_Solve (12). The optimization tool consists of four components: pavement database, data preparation, optimization analysis and results output. The pavement database stores current and historical pavement conditions, project history, and road inventory data. The data preparation component enables the user to define pavement condition states (Excellent, Good, Fair, Poor, and Very Poor) by selecting the corresponding PCR thresholds; to generate the current pavement condition distribution table for further analysis; and to determine the year from which historical condition data are used to generate the Markov transition probability matrices. The optimization analysis component allows the user to select the proper pavement network for optimization; to input unit cost for each type of repair treatment; to choose appropriate objective functions; to set pavement condition constraints; to select allowable treatments for pavements in different condition states; and to enter the maximum available budget for each year. The results output component enables the user to view the projected pavement condition distribution, the optimized recommended treatment policy, and the corresponding budget allocation.
EXAMPLE PROBLEMS

This section presents three example problems solved by the optimization tool developed in this study. For the example runs, ODOT’s priority system pavement network which consists of 11,941 lane miles of interstate highways, U.S. routes, and state routes is analyzed over the next 20 years. The unit costs of the four types of repair treatments, per lane-mile, are: $40,000 for PM, $100,000 for Thin Overlay, $200,000 for Minor, and $1,000,000 for Major.

Pavement conditions are classified into five categories based on PCR scores as shown in Table 1.

<table>
<thead>
<tr>
<th>Pavement Condition</th>
<th>PCR score range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>PCR &gt;= 85</td>
</tr>
<tr>
<td>Good</td>
<td>75 &lt;= PCR &lt; 85</td>
</tr>
<tr>
<td>Fair</td>
<td>65 &lt;= PCR &lt; 75</td>
</tr>
<tr>
<td>Poor</td>
<td>55 &lt;= PCR &lt; 65</td>
</tr>
<tr>
<td>Very Poor</td>
<td>PCR &lt; 55</td>
</tr>
</tbody>
</table>

Pavements in poor and very poor conditions are considered to be “deficient”. The current network deficiency level is 2.7%.

Example 1. Minimum Budget to Achieve a Desired Condition Level

Example 1 is to calculate the minimum budget required to improve the overall pavement network condition by reducing the deficiency level from 2.7% to 1% within three years and to determine the corresponding fund allocation among different maintenance and rehabilitation treatments. Both the optimized results with and without budget constraints are analyzed and compared. Table 2 shows the allowable treatments for Example 1.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Do Nothing</th>
<th>PM</th>
<th>Thin Overlay</th>
<th>Minor Rehab</th>
<th>Major Rehab</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Good</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Fair</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Poor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Very Poor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

The optimization model without budget constraints (Model A) yields a theoretical optimized solution for the problem. Since no maximum available annual budget is defined, the mathematical optimization model could recommend any amount of pavement mileage to be repaired in each year in order to minimize the total cost over the analysis period, which is 20 years in this case. Figure 1 shows the recommended budget allocation for each type of treatment, and the corresponding projected pavement condition distribution.
FIGURE 1 (a) Recommended treatment budget, and (b) pavement condition distribution for Example 1 (without budget constraints).
From Figure 1 (a), it can be seen that the required budget for the year 2013 is $206.7 million, much higher than the other years. Figure 1 (b) indicates that the deficiency level is reduced gradually from 2.7% to 1%. However, this result may not be suitable for practical use, since the recommended budget for the third year may be far beyond the available maximum annual budget. Besides, the recommended annual budget varies significantly in the first several years, which makes the treatment strategy difficult to be implemented by highway agencies. It should be noted that the funds for years after 2014 are used to maintain the deficiency level at 1%, since pavements tend to deteriorate over years.

The optimization model with budget constraints (Model B) provides an optimal solution under the constraint that recommended budgets do not exceed the maximum available budget for each year. In this example run, it is assumed that the annual budget limitation is $150 million. All other constraints and objective functions are the same with the Model A. Figure 2 presents the recommended budget allocation for each type of treatment, and the corresponding projected pavement condition distribution.
FIGURE 2 (a) Recommended treatment budget, and (b) pavement condition distribution for Example 1 (with budget constraints).
It can be seen from Figure 2 (a) that the recommended annual budgets are all within the limit of $150 million during the analysis period. Figure 2 (b) indicates that the deficiency level is reduced gradually from 2.7% to 1% in three years. Although the average annual pavement expenditure is $141 million, which is slightly higher than the theoretical optimized result ($140.6 million) obtained from Model A, this model yields a more practical and stable solution.

Model A provides a maintenance and rehabilitation strategy to minimize the total cost in the 20 years without considering the budget limitation; whereas Model B has one more set of constraints to ensure that the recommended annual budgets do not exceed the maximum available budget limitation. The average annual budget required obtained from Model A is slightly lower than that of Model B, which means Model A yields a better solution than Model B if the total cost in the analysis period is the only consideration. However, taking into account the actual available budget situation, Model B yields a more practical solution.

Example 2. Maximum Network Condition within Given Budget Constraints

Example 2 is to generate the budget allocation plan among various repair treatments to maximize the entire pavement network condition when the available budget level has already been determined. It is assumed that the available annual budget is $140.6 million as calculated by Model A in Example 1, since Model A yields a theoretical optimized result. The objective is to maximize the proportion of pavements in Excellent, Good, and Fair conditions over the whole analysis period. The allowable treatments are the same with Model A in Example 1 (Table 2).

Figure 3 shows the recommended budget allocation among different maintenance and rehabilitation treatments, and the corresponding predicted pavement condition distribution.
FIGURE 3 (a) Recommended treatment budget, and (b) pavement condition distribution for Example 2.

The comparison between the predicted pavement condition levels obtained from Example 1 (Model A) and Example 2 is important, as the total amount of treatment expenditure over the
20 years recommended by the two models is almost the same. Figure 4 shows the comparison of deficiency trends obtained from Example 1 (Model A) and Example 2.

**FIGURE 4 Comparison of deficiency level trends between Example 1 (Model A) and Example 2.**

For Example 2, the objective is to maximize the total proportion of pavements in Excellent, Good, and Fair conditions over the analysis period given the amount of budget each year. Since there are no constraints to control the deficiency level each year, the deficiency level trend is not stable. For Example 1, the objective is to minimize the total cost over the 20 years given the condition level constraints for each year; therefore, the deficiency level is kept at a certain level specified by the user. The average deficiency level derived from Example 1 is 1.16%, which is slightly lower than that of Example 2 (1.24%). The main reason is that the model in Example 1 can spend any amount of money each year to achieve the best solution for the entire analysis period, as budget constraints are not introduced.

**Example 3. Allowable Treatments Effects on Annual Budget Requirements**

Example 3 is a sensitivity analysis to test the impact of different allowable treatments on the required average annual budget to achieve a certain condition target. For instance, the decision-maker is interested in the effect of PM on the average annual budget. The two different sets of allowable treatments are shown in Table 2 and Table 3. While in Table 2 PM is allowed to be conducted on pavements in good and fair conditions, it is not allowed in Table 3.
TABLE 3 Allowable Treatments for Example 3 (Not Allowing PM)

<table>
<thead>
<tr>
<th>Condition</th>
<th>Do Nothing</th>
<th>PM</th>
<th>Thin Overlay</th>
<th>Minor Rehab</th>
<th>Major Rehab</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Good</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Fair</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Poor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Very Poor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Eleven deficiency level scenarios are analyzed for this problem, as shown in Figure 5.

![Impact of PM on required average annual budget](image)

**FIGURE 5** Impact of PM on required average annual budget.

The objective is to minimize the total pavement expenditure in 20 years and the target deficiency level is to be achieved within three years. Budget constraints are not included in the optimization model for Example 3, since the objective is to seek the theoretical minimum budget to achieve a certain deficiency level.

It can be seen from Figure 5 that the impact of PM on the required average annual budget is quite significant. If PM is not allowed to be conducted, it would cost much more money to achieve the same condition level given the allowable treatments specified in Table 2 and Table 3. The approximate differences are $36 million for deficiency level targets below 4% and $17 million for deficiency level targets above 4%.

It should be noted that a sensitivity analysis can also be performed, based on the results shown in Figure 5, to investigate the relationship between condition level target and the required average annual budget. For instance, given the allowable treatments shown in Table 3 where PM...
is not allowed, it can be seen from Figure 5 that when the deficiency level is below 6%, the slope is larger. This means that the required annual budget is more sensitive at lower deficiency levels.

**SUMMARY AND CONCLUSIONS**

The network-level pavement optimization tool presented in this paper is capable of determining the budget requirements to achieve a given overall pavement network condition, and generating funds allocation plan to maximize the pavement condition level. This decision-making tool enables users to select different objective functions and constraints to generate optimized results based on the various analysis needs. The output of the optimization system includes the projected pavement condition distribution, the optimized recommended treatment strategy, the required treatment budget, and the optimized budget allocation plan over the analysis period. The results of the example runs show that this tool can be implemented by highway agencies for the pavement optimization issues at network-level.

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