Infrastructure Condition Assessment and Prediction under Variable Traffic Demand and Management Scenarios

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ABSTRACT

Departments of Transportation (DOTs) are responsible for keeping their road network in a state of good repair while also aiming to reduce congestion through the implementation of different traffic control and demand management strategies. These strategies can result in changes in traffic volume distributions, which in turn affect the level of pavement deterioration due to traffic loading. To address this issue, this dissertation introduces an integrated simulation-optimization framework that accounts for the combined effects of pavement conditions and traffic management decision-making strategies. The research focuses on exploring the range of possible performance outcomes resulting from this integrated modeling approach. The research also applied the developed framework to a particular traffic demand management strategy and assessed the impact of dynamic tolls around the specific site of I-66 inside the beltway. The integrated traffic-management/pavement-treatment framework was applied to address both the operational and pavement performance of the network. Aimsun hybrid macro/meso dynamic user equilibrium experiments were used to simulate the network with a modified cost function taking care of the dynamic pricing along the I-66 tolled facility. Furthermore, the framework was expanded to include the development of a systematic and comprehensive methodology to optimize the allocation of networkwide pavement treatment work zones over space and time. The proposed methodology also contributed to the development of a surrogate function that reduces the optimization computation burden so that researchers would be able to conduct work zone allocation optimization without having to run expensive simulation work. Finally, in this
dissertation, a user-friendly decision-support tool was developed to assist in the pavement treatment and project selection planning process. We use machine learning models to encapsulate the simulation optimization process.
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GENERAL AUDIENCE ABSTRACT

Departments of Transportation (DOTs) are responsible for keeping their road network in a state of good repair. Improvement in pavement rehabilitation plans can lead to savings in the order of tens of millions of dollars. Pavement rehabilitation plans result in work zone schedules on the transportation network. Limited roadway capacities due to work zones affect traffic assignments and routing on the roads, which impacts the selection of optimal operation strategies to manage the resulting traffic. On the other hand, the choice of any particular operation and routing strategy will result in different distributions of traffic volumes on the roads and affect the pavement deterioration levels due to traffic loading, leading to other optimal rehabilitation plans and corresponding work zones. While there have been several research efforts on infrastructure condition assessment and other research efforts on traffic control and demand management strategies, there is a wide gap in the nexus of the two fields. To address this issue, this dissertation introduces an integrated simulation-optimization framework that accounts for the combined effects of pavement conditions and traffic management decision-making strategies. The research focuses on exploring the range of possible performance outcomes resulting from this integrated modeling approach. The research also applied the developed framework to a particular traffic demand management strategy and assessed the impact of dynamic tolls around the specific site of I-66 inside the beltway. The integrated traffic-management/pavement-treatment framework was applied to address both the operational and pavement performance of the network. Furthermore, the framework was expanded to include the development of a
systematic and comprehensive methodology to optimize the allocation of networkwide pavement treatment work zones over space and time. The proposed methodology also contributed to the development of a surrogate function that reduces the optimization computation burden so that researchers would be able to conduct work zone allocation optimization without having to run expensive simulation work. Finally, in this dissertation, a user-friendly decision-support tool was developed to assist in the pavement treatment and project selection planning process. We use machine learning models to encapsulate the simulation optimization process.
Dedication

Micheline and Teta Kodsiye, I know you are cheering me on from above.

This one is for you ...
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Chapter 1: Introduction

Background and Problem Statement

The Virginia Department of Transportation (VDOT) is responsible for more than 128,000 lane miles of roadway. Keeping these miles of roadways in a state of good repair costs around $2.2 Billion annually in Virginia (Virginia Dept. of Transportation 2020). Improvement in pavement rehabilitation plans to minimize costs can lead to savings in the order of tens of millions of dollars. Pavement rehabilitation plans result in project lettings, which translate into work zone schedules on the transportation network. Limited roadway capacities on network links due to work zones affect traffic assignments and routing on the roads, which impacts the selection of optimal operation strategies to manage the resulting traffic. On the other hand, the choice of any particular operation and routing strategy will result in different distributions of traffic volumes on the roads and affect the pavement deterioration levels, leading to other optimal rehabilitation plans and corresponding work zones. Adopting an integrated approach to pavement rehabilitation and traffic operation would result in higher-fidelity models and objective functions. Conducting multi-objective optimization with these higher fidelity models with rehabilitation and operation plans that work in tandem can reduce the rehabilitation cost and reduce the overall system travel times.

There is currently no system that can be used to directly translate the impact of alternative traffic demand and management strategies on pavement conditions, both on the short- and long-term horizons. The objective of this research is to develop an integrated modeling framework that can be used to evaluate the impact of different traffic demand management and operation strategies on pavement conditions and consequently, on required maintenance and
rehabilitation treatments. The research ultimately aims to assist engineers in selecting the traffic operation strategy that would optimize their pavement treatment plans to keep pavement in a state of good repair while minimizing the overall pavement treatment cost and reducing travel times. This creates a dynamic decision-support tool that enables the user to test the outcomes of implementing various operation strategies within different sets of constraints.

**Objective**

While there have been several research efforts on infrastructure condition assessment and other research efforts on traffic control and demand management strategies, there is a wide gap in the nexus of the two fields. As more data, technology, and advancements in computer modeling and simulation are becoming available, it is crucial to understand the impact of traffic control and demand management strategies and the potential resulting shift in intermodal travel on infrastructure health and pavement treatment plans.

The objectives of the dissertation, therefore, are the following:

- Develop an integrated modeling framework that can be used to evaluate the impact of different traffic demand management and operation strategies on pavement conditions and, consequently, optimize required maintenance and rehabilitation treatments.
- Expand on the integrated framework to further consider specific work zone temporal and spatial distributions within the optimization process.
- Develop a smart decision support tool to assist DOTs in their decision-making as they allocate funds to construct and maintain their infrastructure over a given time horizon in response to traffic-related changes.
**Dissertation Organization**

The dissertation goals and objectives are achieved over six different chapters organized as follows (Figure 1). Chapter 1 is an introduction that presents background information, identifies the problem statement, and defines the objective of the research. Chapter 2, “A Simulation-Optimization Framework for Integrated Infrastructure Condition and Traffic Management Strategies,” is where the integrated modeling framework is developed and has its impacts illustrated with a case study in Fairfax County, VA, USA. Chapter 3, entitled “An Integrated Simulation-Optimization Framework for Assessing the Impact of I-66 Dynamic Toll Pricing on Pavement Deterioration and Maintenance Decisions”, aims to assess the impact of dynamic tolls around I-66 inside the beltway. Subsequently, after developing and implementing the general framework in the two previous chapters, Chapter 4, “An Optimization Framework for Pavement Treatment and Spatio-Temporal Distribution of Work Zone Closures,” expands on the developed framework to include the effect of work zone closures spatio-temporal distribution. This chapter has two major objectives: (1) to develop a systematic and comprehensive methodology to optimize the allocation of networkwide pavement treatment work zones over space and time and (2) to develop a surrogate function to reduce the optimization computation burden so that researchers would be able to conduct work zone allocation optimization without having to run expensive simulation work. At last, Chapter 5, “Encapsulation of the Simulation Optimization Process Using Machine Learning,” captures the simulation optimization process using machine learning/artificial intelligence models and demonstrates the process with an example. The final chapter of this dissertation, Chapter 6, summarizes the dissertation findings and provides insights into the direction of future work.
Figure 1. Dissertation Organization
Chapter 2: A Simulation-Optimization Framework for Integrated Infrastructure Condition and Traffic Management Strategies

Abstract

The Virginia Department of Transportation (VDOT) is responsible for keeping its road network in a state of good repair while also aiming to reduce congestion through the implementation of different traffic control and demand management strategies. These strategies can result in changes in traffic volume distributions, which in turn affect the level of pavement deterioration due to traffic loading. To address this issue, this paper introduces an integrated simulation-optimization framework that accounts for the combined effects of pavement condition and traffic management decision-making strategies. The research focuses on exploring the range of possible performance outcomes resulting from this integrated modeling approach. The authors illustrate the proposed framework and provide a case study analysis in Virginia, USA. The results showed that the optimized model could achieve a maximum Critical Condition Index (CCI) increase from an average of 65 to 100, causing about 80% of travel time increase. On the other hand, a do-nothing approach preserves travel time but decreases the CCI by seven points on average during one fiscal year. The use of the proposed framework is therefore crucial for decision-making purposes and can help DOTs understand the trade-off involved when considering traffic management and pavement performance.

Introduction

Departments of Transportation (DOTs) strive to reduce congestion on their road networks, implementing different traffic operations, control, and travel demand management strategies. While these strategies result in changes in travel demands, travel route choices, and travel mode selections, and while the condition of the pavement is obviously related to the traffic loading, there is currently no system that can be used to directly translate the impact of alternative traffic demand and management strategies on pavement conditions, both on the short- and long-term horizons.

This research aims to develop an integrated modeling framework that can be used to evaluate the impact of different traffic demand management and operation strategies on the pavement conditions and, consequently, on required maintenance and rehabilitation treatments. The research ultimately aims to produce a tool that can assist DOT engineers in selecting the traffic operation strategy to optimize their infrastructure conditions and operational performances.

This paper discusses the development of a system that can be used for comparing different operation strategies, focusing more on exploring the range of possible performance outcomes resulting from this integrated approach. The paper illustrates the impacts of adopting the proposed framework with a case study on a selected network in Fairfax County.

Background

Travel demand management (TDM) influences travelers' departure, travel mode, and route choices. Traffic control (TC) manages vehicles on the road to improve transportation system performance (travel time and reliability, throughput, delay, safety, etc.). Existing literature shows several examples of the implementation of traditional and innovative TDM and
TC strategies in the US and Europe (1-6). Research areas also include urban control strategies, signal priority (7, 8), large-scale control (9), and travel time estimation (10). However, none of these studies attempted to quantify or link these strategies to potential changes in pavement conditions (due to different network traffic load distributions) or how many changes in funding allocations/distributions need to be made as a result. This research is intended to fill this gap, by developing a framework that allows the evaluation of different strategies.

Methods

A. Traffic-Pavement Interaction

Traffic management and control strategies and pavement condition deterioration models interact in a closed-loop system (Figure 2).

- The application of different traffic management and control strategies results in different traffic volume distribution on the transportation network. This, in turn, would lead to different deterioration of pavement conditions due to the different traffic loading associated with these different strategies.

- Applying an optimization program to determine the best pavement treatment plans would result in different repair/treatment schedules on the transportation network, leading to different work zone temporal and spatial distributions and, hence, temporarily reduced capacities on different network links. This, in turn, will result in different optimal traffic distribution on the network.
B. Integrated Simulation Framework

The integrated system consists of three interlinked main elements:

- A central database
- A decision-support (optimization) tool
- A simulation tool (Aimsun)

The framework is the basis for the application of an advanced system that would incorporate the complete dataset and account for different traffic demand management and control strategies. In the following, the development of the deterioration model will be discussed, followed by details on the optimizer and the Aimsun simulation.
C. Pavement Deterioration Model

In this paper, we use a case study from Virginia, USA, to illustrate the concept. Virginia DOT (VDOT) uses Pavement Performance Prediction Models (PPPM) in order to anticipate future pavement conditions and accordingly plan for different maintenance activities. VDOT uses a Critical Condition Index (CCI) deterioration model that computes future CCI values based on pavement age and its last treatment type as follows (11):

\[ CCI(t) = CCI_0 e^{-a \cdot t \cdot b \cdot c(t)} \]  

where

- \( CCI_0 \): CCI immediately after treatment
- \( t \): Years since last treatment activity
- \( a, b, c \): PPPM coefficients

These currently used concepts are important, but they need to be expanded upon to incorporate the effect of traffic distribution on the network, in addition to the effect of each treatment on the pavement condition. For example, (12) developed a model that describes CCI deterioration as a function of time but also includes the Modified Structural Index (MSI) as an input in its formulation.

\[ CCI_{Model} = 100 - T^{\beta_0 e^{(\beta_0 + \beta_1 + \beta_2 + \beta_3 \cdot T)}} \]  

Where

- \( T \): Time in years
- \( MSI \): Modified Structural Index value
- \( \beta_0, \beta_1, \beta_2 \) and \( \beta_3 \): Calibration factors (\( \beta_0 = 1.7027, \beta_1 = 0.049, \beta_2 = 0.0866, \beta_3 = 0.1595 \))

In this equation, the Modified Structural Index is computed as follows:
\[ MSI = \frac{SN_{eff}}{SN_{req}} \left( \frac{0.4728(D_0 - D_{1.5H_p})^{-0.4810} H_p^{0.7581}}{0.05716 \left[ \log(ESAL) - 2.32 \log(M_r) + 9.07605 \right]^{2.36777}} \right), \] (3)

where

\[ D_0: \text{ FWD deflection under the applied load} \]
\[ H_p: \text{ Total pavement depth (i.e., measured from the top of the pavement to the top of the subgrade)} \]
\[ D_{1.5H_p}: \text{ FWD deflection at a distance equal to 1.5 times the total pavement depth} \]
\[ M_r: \text{ Resilient modulus calculated using FWD measurements} \]
\[ ESAL: \text{ Equivalent Single Axle Load} \]

The ESAL is generally calculated as follows:

\[ ESAL = AADT \times V_f \times G \times D \times L \times 365 \times Y, \] (4)

where

\[ AADT: \text{ Annual Average Daily Traffic} \]
\[ V_f: \text{ Vehicle axles factor for the flexible pavement with the given car/truck mix} \]
\[ G: \text{ Growth factor set to 3\% over a 20 years period} \]
\[ D: \text{ Directional factor set at 0.5} \]
\[ L: \text{ Lane factor set at 0.9} \]
\[ Y: \text{ Number of years in the design period set to 20} \]

Equation (2) has a general form that makes it suitable for improvement and incorporation of traffic load impact. Equation (3), on the other hand, accommodates traffic volume through ESAL in the MSI equation but does not account for different treatment types. Consequently, in this paper, the model from (2) was expanded to include the traffic effect, expressed in terms of AADT, as shown in (5) below:
\[ CCI(t) = CCI_0 e^{a \cdot b \cdot v(t) \cdot (t - t_{last})} \]  \hspace{1cm} (5)

where

\[ CCI_0: \text{CCI immediately after treatment} \]
\[ t: \text{Years since last treatment activity} \]
\[ a,b,c,d,e: \text{Coefficients (as shown in Table 1)} \]
\[ v: \text{AADT} \]

Equation (5) was calibrated against (2) with an assumed average \( SN_{eff} \) and \( M_r \) values taken from the PMS data for asphalt interstate segments. By minimizing the SSE (Sum of Squares due to Errors), coefficients \( d \) and \( e \) were determined (Table 1). With the new model, ESAL being a function of AADT, its impact will be absorbed by the \( d \) and \( e \) coefficients.

D. Treatment Implication

Maintenance and rehabilitation (M&R) treatments are used to reestablish the performance of deteriorated pavement. Different treatments are applied to pavement depending on the pavement damage severity. These treatments include:

- Do Nothing (DN)
- Preventive Maintenance (PM)
- Corrective Maintenance (CM),
- Restorative Maintenance (RM), and
- Rehabilitation or Reconstruction (RC).

As expected, there are different costs associated with different treatment categories (13). In addition, maintenance activities will result in work zones requiring lane closures. Following a conversation with VDOT pavement specialists, an approximate estimation of the duration of each treatment category was provided. Assuming that closure will occur one lane at a time, the
estimated durations were used to compute equivalent lane closures (per lane mile) spread over the time step duration considered in this paper's case study (three months).

In addition to increasing the CCI value, different treatments result in a different deterioration curve. According to Dell'Acqua, CM, RM, and RC reset the age of the pavement, and increase the CCI value to a 100, whereas a PM treatment does not reset the pavement age, and increases the CCI value by eight points (11) (Table 2).

Table 1. Coefficients of CCI Deterioration Model

<table>
<thead>
<tr>
<th>Treatment</th>
<th>a*</th>
<th>b*</th>
<th>c*</th>
<th>d</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM**</td>
<td>9.176</td>
<td>9.18</td>
<td>1.27295</td>
<td>0.53972</td>
<td>-0.02914</td>
</tr>
<tr>
<td>RM</td>
<td>9.176</td>
<td>9.18</td>
<td>1.25062</td>
<td>0.53972</td>
<td>-0.02914</td>
</tr>
<tr>
<td>RC</td>
<td>9.176</td>
<td>9.18</td>
<td>1.22777</td>
<td>0.53972</td>
<td>-0.02914</td>
</tr>
</tbody>
</table>

* as obtained from (11)
**PM assumed to deteriorate similar to CM (11)

Table 2. Treatment Implications

<table>
<thead>
<tr>
<th>Treatment</th>
<th>CCIs after Treatment</th>
<th>Cost per lane mile ($)*</th>
<th>Three-month closure per lane mile (lane)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DN</td>
<td>CCI=CCI</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PM</td>
<td>CCI=Min (CCI+8, 100)</td>
<td>25257</td>
<td>0.0333</td>
</tr>
<tr>
<td>CM</td>
<td>CCI=100</td>
<td>93484</td>
<td>0.0333</td>
</tr>
<tr>
<td>RM</td>
<td>CCI=100</td>
<td>171488</td>
<td>0.0417</td>
</tr>
<tr>
<td>RC</td>
<td>CCI=100</td>
<td>470357</td>
<td>0.0667</td>
</tr>
</tbody>
</table>

* From Chowdhury (13)

E. Optimization Tool

The proposed system accounts for the effect of pavement deterioration due to traffic volume and age on the pavement condition and cycle. In addition, it reflects the effect of different traffic levels dictated by the chosen control strategy. The critical condition index CCI is used as the performance metric for the purpose of the pavement evaluation. The decision-support tool conducts an optimization to maximize the overall CCI values across the different segments considered. Figure 3 shows the overall optimization algorithm. The optimizer decision variables are the pavement treatment type and location of treatment over the next time horizon. This results in (1) work zone schedules on the network, reducing capacity on the selected links, and
(2) changes in future CCI deterioration curves (an immediate increase in link CCI value portraying the impact of the selected treatment, and a new pavement deterioration curve).

A key factor to be emphasized in this framework is the expansion of the optimization problem in time, where each simulation at time step 't+1' is based on the optimizer treatment decisions made at time 't'.

Consequently, the framework tested in this paper will similarly be implemented in the decision-support tool that will assess the effect of implementing each traffic strategy and treatment at their respective times on both objectives:

- Improved pavement condition
- Reduced congestion

Figure 3. Overall Optimization Algorithm
Pyomo framework was used to code the optimization problem. Network attributes (length, number of lanes), volume distribution, and pavement attributes (CCI) data was used as an input. The optimizer generated, for each run, treatment plan, and roadway closures for the upcoming time period.

The optimization considered multiple time steps and assessed treatment needs at the beginning of each time step. Optimization of each quadrant resulted in lane closures, that ultimately affected the capacities of each road segment. This, in turn, resulted in different route choices, and therefore different volumes on each possible route. Each of these solutions was associated with different costs. The optimizer maximized the sum of CCI values, while using these costs and budget constraint to determine the optimal treatments for each quadrant.

In other words, the problem was formulated as follows:

**Sets:**

L: set of links in the overall network,

I: set of treatment types corresponding to DN, PM, CM, RM, and RC.

**Decision Variable:**

\( x_{il} \): binary variable. Equals 1 if treatment i (i∈I) is applied to link l (l∈L)

**Constraints:**

CCI on link l

\[
CCI_l = \sum_i x_{il} \times [CCI_0 - e^{-a_l - b_l c_l^{ln(t_l)}} - d(v) e_l] \forall l,
\]

\(a_l, b_l, c_l, d_l,\) and \(e_l\) as defined before (Table 1)

\[
CCI_l \leq 100 \forall l.
\]
\[
\sum_l \sum_i x_{il} \cdot co_i \cdot le_i \cdot ln_i \leq B, \tag{8}
\]

where
- \( co_i \): cost ($ per lane mile) of applying treatment \( i \in I \)
- \( le_i \): length of link \( l \in L \)
- \( ln_i \): number of lanes of link \( l \in L \)
- \( B \): budget

\[
\sum_i x_{il} = l \quad \forall l \tag{9}
\]

**Objective Function:**

Max \( Z = \sum_l CCI_l \) \tag{10}

F. Aimsun Simulation

A large-scale simulation was performed using Aimsun. The transportation network was imported as a shapefile. Vehicles' origin-destination (O-D) trip data was imported from the MPO planning model. Network volume distribution data was used to calibrate the O-D traffic demand matrices.

Once set up, Aimsun was used to run different scenarios based on roadway closures distribution input from the optimization results. The CCI deterioration computation requires the use of the accumulated link volume over the design period. This accumulated volume varies due to changes in the network. The software package generates traffic volume distribution outputs that feed into the optimization run for the next period. In addition, it produces total travel time and congestion results that are used to assess the system’s operational performance. From roadway closure import to scenario creation and execution to output generation, these steps were coded into Aimsun Python scripting.
Case Study

The developed integrated system was applied to a defined area in Fairfax County to illustrate the impacts of adopting the proposed framework and the range of possible improvements that it could achieve. The area of study, shown in Figure 4, was selected because of the high traffic volumes and different congestion issues in the region. In addition, the area has a transit system and different facilities that can help implement a variety of traffic demand and traffic control strategies in the future.

To minimize the size of the problem, the team selected a subnetwork within the area of study where treatments were assumed to be applied. Figure 5 shows the full Aimsun network and the subnetwork selected for treatment application.

A macroscopic traffic assignment was implemented in Aimsun. The optimization, on the other hand, considered four-time steps. Each time step is defined as a quadrant (four quadrants in a fiscal year, three months each) and specified treatment needs at the beginning of each time step. During each quadrant, the treatment selection required different work zone temporal and spatial distribution, leading to temporally reduced network capacities. These altered capacities were imported by Aimsun’s Python script and used to generate new traffic volume distributions. The latter link volumes were applied in the pavement deterioration model feeding the optimization in the upcoming period.
Results

The integrated simulation system generated a set of pavement treatment schedules for each of the four modeled quadrants. The assigned treatments over the four quadrants (Q1 to Q4) are represented in Figure 6. Quadrant 1(Q1), which started off with the lowest CCI values, required the highest levels of improvement. To achieve higher CCI values across the network within the allocated budget, mostly CM and RM treatments were applied, and fewer RC and PM
were assigned. During the subsequent quadrants, after the CCI values were already raised because of treatments applied during the first quadrant, PM and RC treatments were the most applied to spend the assigned budget while keeping CCI values at a high level.

For the purpose of this application, the simulation runs assumed four representative scenarios during each quadrant, reflecting different durations of different treatment categories (Figure 7). Treatment categories considered ranged from the least aggressive PM to the more aggressive CM, to the aggressive RM, to the most aggressive RC. The higher the aggressiveness of the treatment, the longer the duration of its execution and thus the longer the duration of the resulting closure. As such, scenario R4 shown below represents the case where only closures due to RC were still applied. R3 represents closures from RM and RC, R2 considers the case where CM, RM, and RC works are ongoing, and their respective closures are in place. Finally, R1 represented the scenario when all quadrant closures were carried out, meaning all PM, CM, RM, and RC treatments were ongoing.
Closures dictated by the generated treatment schedules (Figure 6) resulted in different traffic congestion distributions during the different quadrants across the different represented closure scenarios. Congestion outputs were inferred from the Aimsun simulation using volume to capacity ratio (V/C) results. For instance, Figure 8 presents a comparison between the base case scenario where no treatments and no closures were applied and the R1 scenario of quadrant 1,
where all PM, CM, RM, and RC closures were in place. Results clearly show more red links in the Q1 R1 case, where the reduced link capacities caused more roadway segments to experience congestion (red links).

In addition, the system computed travel times across roadway segments during each simulated scenario, and CCI values reflecting pavement performance were computed following the application of the different treatments. Total travel time (TTT) was extracted from the simulation output as a measure of operational performance.

Results from the simulations were used to demonstrate the interaction of pavement and operational performance following the recommendations of the applied framework. Figure 9 illustrates the impacts on CCI as a measure of pavement performance and TTT as a measure of operational performance under three different scenarios: (1) a scenario representing the recommendations of the developed system (max), (2) a random scenario where the pavement budget is randomly spent, and (3) a do-nothing (DN) scenario.
Figure 9. Range of Improvements (CCI vs. TTT)

Discussion

Looking at the range of improvement outputs in Figure 9, during one fiscal year, the optimized model has the potential of achieving a maximum CCI increase from an average of 65 up to a nearly perfect score of 100, causing a TTT increase of about 80%. Conversely, a do-nothing approach (DN) will preserve TTT but cause a CCI decrease of 7 points on average during one fiscal year. Consequently, depending on the intended purpose and primary concerns in a specific area of study, the system could be tailored to target any specified objective within the range of potential improvements.

Finally, and for the sake of comparison, if the system was left to randomly spend the budget without an objective (e.g., to maximize CCI), the range of improvement would be drastically affected. As seen in Figure 9, CCI increases would be limited to 6 points increase as opposed to 35 points in the optimized case, while TTT would still induce a high increase of about 60%. From here, the benefits of the system in providing an optimized pavement condition and operational performance within the allocated budget and specified constraints can be clearly seen.
Conclusions

This paper introduced a developed framework that integrates traffic demand and traffic operation strategies with pavement condition assessment and treatment optimization. In this paper, a CCI prediction model was modified to account for the proposed integrated framework. The Aimsun simulation tool was used to conduct a simulation of a case study network to produce (1) Total travel time performance metric and (2) Modified traffic volume distributions on the transportation network. An optimizer was used to determine the optimum pavement treatment for a given budget, resulting in new scheduled work zones and associated reduced capacities on the selected treatment road segments. This information was fed into the Aimsun simulation to assess the impact of the changes in capacities on the volume distribution for the next time step.

We have shown an illustration of the proposed framework and provided a proof-of-concept study in Northern Virginia. The outputs of the case study displayed ranges of possible improvements in CCI values across the network along with the associated impacts on the total travel time. Preliminary analysis showed that the optimized model could achieve a maximum CCI increase from an average of 65 to 100, causing a travel time increase of about 80%. On the other hand, a do-nothing approach will preserve travel time but cause an average CCI decrease of 7 points during one fiscal year. The framework could be tailored to target specific objectives within the possible range of improvements based on the site-specific requirements. Future work would concentrate on the application of the decision-support tool that would assist VDOT engineers in comparing different transportation demand management and operation strategies in terms of pavement performance, system delay, and other performance metrics (e.g., predicted crash frequencies).
References


Abstract²

Tolled facilities are undoubtedly expected to alter the distribution of traffic across the transportation network. On the other hand, traffic volumes and loading have an impact on deteriorating pavement conditions. These traffic volumes are considered by the Departments of Transportation (DOTs) while allocating annual budgets to maintain and rehabilitate roadway segments to sustain pavement performance targets. This research studies the specific site around I-66 inside the beltway, which newly applied dynamic tolls during AM and PM peak hours. An integrated traffic-management/pavement-treatment framework was applied to address both the operational and pavement performance of the network. Aimsun hybrid macro/meso dynamic user equilibrium experiments were used to simulate the network with the modified cost function taking care of the dynamic pricing along the I-66 tolled facility. An optimization was python coded into pyomo framework to specify the optimal maintenance and rehabilitation treatment plan, taking into account CCI deterioration based on the traffic load distribution on the network. Finally, the results of the simulation showed the importance of having an optimized treatment schedule to achieve optimal pavement performance outcomes, with a difference in CCI index that could range all the way from 68 to 95.

**Introduction**

Traffic congestion is one of the major issues in the majority of United States (US) metropolitan areas. Congestion pricing is a popular strategy used to optimize traffic distribution and drive the network to system optimal performance. As part of the congestion pricing strategies, High Occupancy Toll Lanes (HOT) are becoming increasingly popular in the US (Texas, California, Colorado, etc.), mainly due to the increased proportions of Single Occupancy Vehicles (SOVs) in traffic streams (1–3). The idea behind the HOT strategy is to allow SOVs to use certain lanes (or road segments) at a certain cost (tolls). Generally, these HOT lanes would also be High Occupancy Vehicles (HOV) lanes, meaning that vehicles with 2 (HOV2+), 3 (HOV3+), or more riders would be eligible to use them for free. The toll charged to SOVs at different entry points would adjust dynamically based on traffic demand and throughput to maintain certain levels of speed and level of service (LOS). In some instances, these HOT/HOV lanes run parallel to the general-purpose (GP) lanes, where users would be making a lane choice between the GP lanes and the managed HOV/HOT lanes at specific locations of the roadway link. In other instances, the entire segment would function as HOV/HOT, and alternative routes would follow a completely different path; HOT would then be referred to as express lanes or tolled facilities. In all cases, these lanes are known to bring many benefits. Other than relieving traffic congestion, they can incentivize carpooling, bring in revenue that would be used to fund other transportation projects, make use of the extra capacity when (if) previously operated as HOV lanes, or secure a high-speed alternative during congested periods (1–4).

Regardless of the purpose they serve, the implementation of tolls is undoubtedly expected to alter the distribution of traffic across the transportation network (1, 2). On the other hand, traffic volumes and loading have an impact on deteriorating pavement conditions (5).
Departments of Transportation (DOTs) strive to maintain roadways in a good state of repair to sustain pavement performance targets and consequently allocate substantial budgets for maintenance and rehabilitation treatments. Consequently, while looking at the monetary and operational benefits of toll strategies, it is equally important to keep an eye on the resulting pavement performance impacts to ensure optimal allocation of the treatment budgets.

Research efforts have focused on studying the operational aspects of toll strategies, but very few research efforts have been spent in studying their impact on pavement conditions and consequently on required maintenance and rehabilitation needs. The objective of this research is to highlight the importance of pavement consideration and optimal treatment allocation under a toll implementation strategy. The paper illustrates the concept with a case study on I-66 inside the beltway in Northern Virginia, using a hybrid Aimsun simulation for traffic distribution and analysis and pyomo framework for treatment allocation optimization.

The rest of the paper will be divided as follows. It starts with a brief background on pavement management systems, tolled facilities, and the area of study. Afterward, the methodology is presented to provide details on the Aimsun simulation, optimization, and area of study characteristics. Subsequently, the results of the case study are summarized and discussed. Finally, conclusions and directions of future work are highlighted.

**Background**

Pavement Management Systems

Pavement Management Systems (PMSs) are useful by agencies to determine the maintenance and rehabilitation strategies under constrained budgets. For example, Gowda et al. suggested a PMS model based solely on engineering criteria for budget prioritization (6). All states in the US now have a PMS (7). Pavement conditions data is one of the most important data
used to assist the decision-making process. The current practice largely depends on labor-intensive manual pavement condition surveys. Nowadays, vehicles equipped with automatic nondestructive detecting technologies are also used to assess pavement conditions (8, 9). There are several pavement condition indices, e.g., Present Serviceability Rating (PSR), Present Serviceability Index (PSI), Pavement Condition Index (PCI), International Roughness Index (IRI), and Critical Condition Index (CCI).

VDOT uses and aggregates two individual distress data for assessing pavement conditions: Load Related Distress Rating (LDR) and Non-Load Related Distress Rating (NDR). The CCI is calculated as the lower of the two indices. Of special interest to this project is the LDR that incorporates pavement distresses associated with vehicle-load-related damages, including fatigue cracking, patching, rutting, etc. CCI ranges between 0 and 100, with 0 referring to total failure and 100 indicating perfect pavement conditions (10).

Currently, CCI is obtained through data collected and processed by VDOT's contractor, Fugro-Roadware Inc., using image processing technologies and automated sensors. VDOT keeps track of the state of pavement to meet statewide performance targets (e.g., 82% in fair condition or better and 85% in sufficient ride quality for the interstate system). Meeting these targets requires optimization of pavement maintenance activities on the Interstate and Primary network (11).

Tolled Facilities

Many studies have addressed HOT or tolled facilities in general (3, 4, 12–14), and few have targeted HOT inside the beltway (1, 2). Most of these studies confirm the positive impact that this methodology has had on traffic distribution, congestion, and travel time reliability. Among those studies, some researchers focused on the pricing strategy (13, 15, 16), others
focused on the driver behavior and choice of using these facilities \((4, 14, 17)\), while others looked at the impact they have on operations, the accompanying usage trends, or modeled them to test the impact of proposed pricing or behavioral framework \((18–20)\).

Nohekhan et al. wrote one of the papers that studied I-66 inside the beltway. Their research focused on evaluating the operational performance of the tolled facility and its alternative routes. It also offers a comparative analysis between the current HOT as opposed to the previous HOV strategy on I-66 \((1)\). Cetin et al., on the other hand, who also addressed the I-66 study area, were concerned with the investigation of the frequency of usage of the facility and the value of time savings of its users. The study relied on complete toll transactions and probe speed data \((2)\).

In all cases, none of the studies has addressed the possible impacts on pavement performance that would accompany the operational changes. This paper fills this gap by highlighting the importance of pavement consideration in the context of tolled facilities.

Area of Study: I-66 Inside the Beltway

Virginia is among the states that have started implementing these HOV/HOT lanes. One particular application is the I-66 inside the Beltway (Figure 10). The area lies along interstate 66 (I-66) between I-495 and Route 29 in Rosslyn. The site has been a subject of interest for several years, being a major corridor linking Northern Virginia suburban area to the business districts in Arlington and Washington DC, especially that Washington DC was ranked by the INRIX and Texas A&M transportation institute's urban mobility scorecard as the area with highest traffic congestion \((21)\). As of 2013, Active Traffic Demand Management (ATM) systems were being installed on I-66 inside the beltway, namely advisory variable speed limits (AVSL), lane use control signals (LUCS), and hard shoulder running (HSR) \((22)\). Similarly, tolled lanes were
among the projects implemented on I-66 inside the beltway, starting December 4, 2017. The tolling policy is implemented during peak hours and in the peak direction. From Monday through Friday, HOV/HOT operates from 5:30 am to 9:30 am in the eastbound direction and from 3 to 7 pm in the westbound direction. On weekends and outside these hours, the lanes are open for general use (23). The facility is divided into four segments, and consequently, four gantries where vehicles could enter the lanes. Vehicles using the corridor must be equipped with a transponder (EZ pass), which is a radio frequency identification system that would detect the vehicle and charge it with the toll. Vehicles would be charged the toll at the different gantries; consequently, their charge is a function of their entry and exit location. Toll prices are dynamically updated every 6 min depending on the existing traffic volume to ensure a minimum desired speed on the toll lanes of 55 mph according to Nohekhan et al. (1) and 45 mph according to Cetin et al. (2). Alternative routes to the I-66 beltway include Routes 7, 50, 123, 193, and the George Washington Memorial Parkway (24). The metro orange and silver lines also run parallel to the facility and can be considered an alternative choice (2). The tolled facility, however, offers free entry to HOVs and buses, providing them with a faster and more reliable travel alternative. Besides, the Commuter Choice program has implemented several strategies encouraging these non-SOV modes. As a result, between 2015 and 2019, the corridor has witnessed an increase in people throughput by 1.2%, while vehicle throughput decreased by 2.7% during the morning rush hour (25). Widening projects are proposed for parts of the facility depending on its performance in the upcoming years but their implementation is not before 2025 (26).
Methods

Traffic-Pavement Interaction

The application of different traffic demand management and traffic operation strategies, namely the tolled facilities in this paper, would result in different traffic volume distribution on the transportation network. This, in turn, would lead to different deterioration of pavement conditions due to the different traffic loading associated with these different strategies. As such, and in order to account for this traffic-pavement interaction, we propose the use of our integrated pavement modeling and traffic simulation framework. The framework incorporates three main components:

1) Aimsun simulation package where a hybrid macro/meso simulation is performed to model the effect of the tolls and the flow of traffic

2) Optimization tool where pavement deterioration is modeled and an optimal treatment allocation takes place

3) A central database where all the data is stored
The integrated simulation framework links these three main elements together and defines the flow of information among them. In brief, the flow of data throughout the framework components is processed as follows. With the tolls in place, Aimsun provides the volume distribution across the considered network, following a macro/meso dynamic user equilibrium simulation. This initial volume distribution data, along with collected pavement performance (CCI) data are input into the optimizer. The optimizer analyzes the pavement performance data along with the traffic loading data and outputs an optimized roadway closure schedule that feeds into Aimsun. Aimsun produces new volume distribution leading to new CCI deterioration predictions. The cycle can continue for as many simulation periods as needed. For the purpose of illustrating the value of the framework shown in this paper, only one round was needed to show significant improvement in pavement performance when treatment allocation was optimized. Figure 11 is a simplistic representation of the flow of information within the framework.

![Figure 11. Flow of Information in the Integrated Simulation System](image-url)
Aimsun Simulation

The goal of this study was to model the impact of a tolled facility on the traffic distribution and the pavement deterioration in its surrounding area. For that purpose, Aimsun simulation software was selected due to its ability to conduct large-scale macroscopic, mesoscopic, and microscopic simulations in a reasonable time, model the effect of the tolled facility through modified cost functions, and utilize a powerful python-based scripting engine.

To set up the Aimsun simulation, the transportation network and demand data needed to be imported into the software. Using Aimsun GIS importer, the transportation network was imported into Aimsun as a shapefile (Figure 12). Next, the traffic demand was imported from CSV data files of vehicles' origin-destination (O-D) trip data. Finally, traffic demand data were calibrated against available network-loaded volume distribution data.

![Figure 12. Aimsun Network imported from GIS](image)

To account for the tolled facility, the cost functions assigned to the links pertaining to the I-66 inside the beltway were modified to include the effect of the toll price and the vehicle value
of time. When conducting dynamic microscopic and mesoscopic simulations in Aimsun, a link cost function describes the perceived cost of traversing a road section. By default, travel time is used to define the cost of different links. In addition, on the tolled links, the function was modified to add a calibrated toll price time value equivalent. I-66 inside the Beltway applied dynamic pricing during the AM and PM periods. In this paper, the AM period was simulated, and the dynamic toll price was calibrated as a function of flow rate, as shown in Figure 13. The different data points represent median toll pricing and flow rate data during morning peak hours, as retrieved from (1). Regression analysis was conducted and resulted in the model shown in Equation (1).

\[ \text{Toll} = 0.0114 \times \text{Flow Rate} - 17.049 \]  

(1)

Where

- **Toll**: Toll price ($) 
- **Flow Rate**: traffic flow rate (veh/hr)

![Figure 13. Toll Price Calibration](image-url)
To mimic the dynamic pricing on I-66, dynamic user equilibrium was modeled in Aimsun using 6-min time intervals (similar to I-66 toll update interval). The toll price addition to the cost function was coded based on Equation (1), with the flow rate set to be the flow rate output of the previous time interval (section.getStaFlow). This price component was converted to its travel time equivalent by dividing Equation (1) by the value of time assumed at $38/hr (assumed using ranges [$38/hr-$62/hr] from (2)).

Finally, in order to apply the simulation to the area around I-66 while taking into account the traffic movement in the larger neighboring area, a hybrid macro/meso dynamic user equilibrium simulation run was conducted. As shown in Figure 14, the mesoscopic "simulation area" is delineated by the blue polygon, and the rest of the network is modeled macroscopically.

Figure 14. Aimsun Hybrid Macro/Meso Simulation
Pavement Treatment Optimization

Our optimization module aimed at generating an optimal treatment schedule based on the CCI data (pavement condition) and traffic distribution data (applied load). For that purpose, a CCI pavement deterioration model that takes into account the effect of traffic was used. The different treatment alternatives currently used by the Virginia Department of Transportation (VDOT) were considered, and finally, the optimization was coded into a pyomo framework (27, 28).

Pavement Deterioration Model

This paper used a pavement deterioration model that was developed under VDOT project # 467100. The model was calibrated to include the traffic effect, expressed in terms of AADT in addition to the effect of pavement age, as shown in Equation (2) below:

$$CCI(t) = CCI_0 - e^{a - b \cdot \ln(t)} - d(v)^e$$

Where

$CCI_0$: CCI immediately after treatment

$t$: Years since last treatment activity

$a, b, c, d, e$: Coefficients (as shown in Table 3)

$v$: AADT

Table 3. Coefficients of CCI Deterioration Model

<table>
<thead>
<tr>
<th>Treatment</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corrective Maintenance (CM)**</td>
<td>9.176</td>
<td>9.18</td>
<td>1.27295</td>
<td>0.53972</td>
<td>-0.02914</td>
</tr>
<tr>
<td>Restorative Maintenance (RM)</td>
<td>9.176</td>
<td>9.18</td>
<td>1.25062</td>
<td>0.53972</td>
<td>-0.02914</td>
</tr>
<tr>
<td>Rehabilitation / Reconstruction (RC)</td>
<td>9.176</td>
<td>9.18</td>
<td>1.22777</td>
<td>0.53972</td>
<td>-0.02914</td>
</tr>
</tbody>
</table>

* as obtained from (29)
** Preventive Maintenance (PM) assumed to deteriorate similar to CM (29)
**Treatment Implication**

Deteriorated pavement will require maintenance and rehabilitation (M&R) treatments to reestablish its performance requirements. Treatment categories vary by severity and type of activities involved. Typical M&R treatments range from Do Nothing (DN) and the least severe Preventive Maintenance (PM) to Corrective Maintenance (CM), Restorative Maintenance (RM), to Rehabilitation or Reconstruction (RC), which require full reconstruction.

These different treatment categories incur different costs based on their respective activities (5). On the other hand, all types of treatments are supposed to improve the condition of the pavement and, consequently, the CCI value. CM, RM, and RC are assumed to restore CCI to 100 and the age to zero, whereas a PM treatment is considered to result in an eight-point CCI improvement without resetting the age (29) (Table 4).

<table>
<thead>
<tr>
<th>Treatment</th>
<th>CCI(_0) after Treatment</th>
<th>Cost per lane mile ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do Nothing (DN)</td>
<td>CCI(_0)=CCI</td>
<td>0</td>
</tr>
<tr>
<td>Preventive Maintenance (PM)</td>
<td>CCI(_0)=Min (CCI+8, 100)</td>
<td>25257</td>
</tr>
<tr>
<td>Corrective Maintenance (CM)</td>
<td>CCI(_0)=100</td>
<td>93484</td>
</tr>
<tr>
<td>Restorative Maintenance (RM)</td>
<td>CCI(_0)=100</td>
<td>171488</td>
</tr>
<tr>
<td>Rehabilitation / Reconstruction (RC)</td>
<td>CCI(_0)=100</td>
<td>470357</td>
</tr>
</tbody>
</table>

* From Chowdhury (5)

**Optimization of Treatment Plan**

The optimization problem was coded into a Pyomo framework using Python programming language. The system required input data from the central database, namely: network attributes (length, number of lanes), volume distribution, and pavement attributes (CCI) data. Upon execution of the simulation code in python, the optimizer generated the upcoming treatment plan and roadway closures.

Treatment selection resulted in lane closures that eventually affected volume distributions and travel times coming out of the Aimsun simulation. In addition, these treatments incurred
different costs that were evaluated against the available budget. As such, the objective of the optimization was set to maximize the sum of CCI on the different links. The allocated budget was set as a constraint to evaluate how the treatment plan and schedule would fall within the allocated budget. Consequently, in mathematical terms, the optimization problem could be written as follows:

Consider \( L \) to be the set of links in the overall network, and \( I \) the set of treatment types corresponding to DN, PM, CM, RM, and RC, respectively. The following variables, objectives, and constraints will apply.

**Decision Variable:**

\( x_{il} \): binary variable taking the value 1 if treatment \( i \) (\( i \in I \)) is applied to link \( l \) (\( l \in L \))

**Constraints:**

CCI on each link \( l \) at the end of each analysis period would be computed as

\[
CCI_l = \sum_i x_{il} \left[ CCI_{0l} - e^{a_i - b_i - c_i l_{il} + d_i v_l} \right] \forall l
\]

Where \( a_i, b_i, c_i, d_i, \) and \( e_i \) correspond to the deterioration coefficients for treatment \( i \) (\( i \in I \)) (Table 3)

CCI constraint: \( CCI_{il} \leq 100 \forall l \)

Budget Constraint: \( \sum_i \sum_l x_{il} \cdot co_i \cdot l_{il} \cdot n_{il} \leq B \)

Where

\( co_i \): cost (\$ per lane mile) of applying treatment \( i \) (\( i \in I \))

\( l_{il} \): length of link \( l \) (\( l \in L \))

\( n_{il} \): number of lanes of link \( l \) (\( l \in L \))

\( B \): budget

One treatment per link constraint: \( \sum_i x_{il} = 1 \forall l \)
Objective Function:

Maximize sum of CCI: \( \text{Max } Z = \sum_l CCI_l \ast l e_l \ast l n_l \)

Area of Study

The area of study was concentrated around the I-66 tolled facility and its neighboring network. The entire network shown in Figure 15 was simulated macroscopically, and the defined simulation area was modeled mesoscopically. All treatment applications and pavement considerations were concentrated around the selected simulated area.

![Figure 15. Area of Study Including I-66 Inside the Beltway](image)

Data for the considered area included toll data, travel demand, roadway network information, and pavement conditions data. Toll data was retrieved from (I) as explained earlier and used for the toll price calibration. Both travel demand and roadway network data were
provided by the Metropolitan Washington Council of Government/Transportation Planning Board (COG/TPB). Travel demand data included vehicles O-D trip data retrieved from version 2.3.75 travel model simulations. Roadway network data, on the other hand, was comprised of roadways geometry and attributes information (such as capacities, posted speeds, number of lanes, etc.), in addition to traffic volumes data which were used to calibrate the O-D matrix in Aimsun. As for the pavement data, it was acquired from virginiaroads.org as pavement condition data which contained CCI values. The roadways pavement characteristics were matched with the pavement network characteristics using a "spatial join" function in Arc Map.

**Results**

Effect of Toll on Traffic Distribution

In order to illustrate the impact of the tolled facility on the traffic distribution, two scenarios were modeled in Aimsun. During the first scenario (No Tolls), no tolls were assumed, and the cost functions in Aimsun were reset to default settings, defining the cost function based on travel time only. For the second scenario (Tolls), dynamic toll pricing was applied to I-66, as explained earlier.

As expected, the two scenarios resulted in a different distribution of traffic across the network. Looking at the differences in congestion levels between both scenarios, based on volume to capacity ratio (V/C) results, the most significant differences are observed around the area surrounding I-66. As shown in Figure 16, following the application of tolls, segments that witness the most decrease in V/C ratios and most congestion relief lie along I-66 itself (blue), whereas the most increased congestion levels were observed along the surrounding road segments (red). That being said, this difference in traffic distribution would lead to different pavement deterioration outcomes. For that purpose, it is very important to carefully optimize
pavement treatments, taking into account the traffic distribution specific to the applied traffic demand strategy—the tolled I-66 facility in this case.

![Figure 16. Differences in Congestion Levels Following the Application of Tolls](image)

Pavement Implication

The integrated traffic-pavement framework was applied to the area of study, considering the tolled I-66 facility during the three-hour AM period. The initial network with the calibrated demand distribution was simulated at first. Volume distribution results following the hybrid macro/meso dynamic simulation were recorded and transferred to the optimizer. In addition, total travel time (TTT) values were recorded from Aimsun outputs. Afterward, the optimization tool provided an optimal treatment plan for the best pavement performance (max CCI), as shown in Figure 17. This plan resulted in an increase in CCI from 73 to 95 following its application (Table
5). Capacity changes based on the treatment plan were input into Aimsun, and the new volume distribution and TTT outputs were again recorded.

![Figure 17. Optimized Treatment Plan (Max CCI)](image)

On the other hand, and in order to illustrate the importance of having the optimal treatment plan in place, the optimization was reversed to spend the entire budget while minimizing CCI. As shown in Figure 18, the resulting treatment plan was very different from the one obtained in Figure 17, with a lot more PM treatments. Even with the entire budget spent, the CCI only improved by three points in this case. Finally, with a Do Nothing scenario, the CCI
would decrease to 68.5, given the distribution of volumes in the presence of tolls, during the analysis period. CCI and TTT results from the optimization and Aimsun simulations in the different cases are summarized in Table 5.

![Figure 18. Treatment Plan (min CCI)](image)

<table>
<thead>
<tr>
<th>Table 5. Simulation Results: CCI Vs. TTT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCI</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>Initial</td>
</tr>
<tr>
<td>Max CCI</td>
</tr>
<tr>
<td>Min CCI</td>
</tr>
<tr>
<td>Do Nothing (DN)</td>
</tr>
</tbody>
</table>
Discussion

Tolled facilities influence the traffic and congestion distribution across a transportation network. I-66 inside the beltway has been recently converted into a tolled facility during AM and PM periods, where its dynamic pricing strategy guarantees a minimum speed during those operations. As such, while congestion on I-66 would be relieved with toll application, neighboring routes would be expected to carry on the converted vehicles volumes and consequently witness higher congestion levels. In other words, the pattern of traffic congestion would be altered with the application of tolls as a demand management strategy.

Nevertheless, even when operational performance target outcomes are achieved with the toll application, the change in traffic load distribution and its effect on pavement deterioration still needs to be addressed. Authorities would not want to make monetary and performance gains with toll applications at the expense of pavement performance and treatment budget spendings. Given the effect of traffic loading on pavement deterioration, it is very important the pavement maintenance and rehabilitation plan be optimized to accommodate the specific needs of the site, based on the resulting traffic volume distribution and the prevailing pavement performance and its history.

In an attempt to highlight the range of possible performance outcomes that authorities could end up having, depending on the way they spend their budget, two different scenarios were compared. In the first scenario, our developed optimization tool was used to achieve the best possible pavement performance, meaning the highest possible average CCI given a specific allocated budget. In the second scenario, the tool was set to make sure the entire budget is spent while minimizing performance. As a result, it turned out the resulting treatment plans were very different (Figure 17 vs. Figure 18). When optimizing performance, many links were allocated
CM treatments while others were assigned PM treatments to achieve the most possible improvement within the available budget during that period (Figure 17). On the contrary, with the minimum CCI scenario, more links received treatments, mostly PM, spending the entire budget without targeting a pavement performance improvement (Figure 17).

CCI and TTT results are summarized in Table 5. These outcomes indicated that the same budget, if not spent properly, can result in a CCI improvement as low as two points on average (73 initial to 75 CCI), where it has the potential of achieving 22 points increase (73 initial to 95 CCI) with the aid of the optimization tool. From here, it is very important, and especially in congestion-critical study sites, like areas neighboring tolled facilities, to spend serious efforts into optimizing pavement treatment plans to avoid wasting the maintenance budget without achieving the aspired pavement performance.

Finally, operational performance effects during the application of treatments were comparable during the different scenarios, and no significant change in TTT was observed. That does not eliminate the need to monitor operational performance in other studies because depending on the site and the study period, operational effects may be very significant and would need to be addressed.

Conclusions

This paper presents the first step towards pavement performance consideration in the presence of tolled facilities. We have studied the specific site around I-66 inside the beltway, which newly applied dynamic tolls during the AM and PM peak hours. An integrated traffic-pavement framework was applied to address both the operational and pavement performance of the network. Aimsun hybrid macro/meso dynamic user equilibrium experiments were used to simulate the network with the modified cost function taking care of the dynamic pricing along
the I-66 tolled facility. An optimization was python coded into pyomo framework to specify the optimal maintenance and rehabilitation treatment plan, taking into account CCI deterioration based on the traffic load distribution on the network.

The results of the simulations of the selected network with and without the application of tolls demonstrated the difference in congestion distribution under the two scenarios. This highlighted the importance of considering traffic load distribution when deciding on a pavement treatment and rehabilitation plan budget allocation. The results from the tested scenarios showed how far off pavement performance could fall if the treatment plan was not strategically developed. It is crucial that the pavement treatment and rehabilitation plan be tailored to the specific case in hand, which is where the role of our developed optimization framework comes into play.

This study opens the door to a vast area of research both within the field of tolled facilities and the consideration for pavement performance that goes with it, and the integration of pavement and operational performance in general. Future research will concentrate on further developing the simulation and optimization framework to provide a holistic view of the interaction both in the long and short term.
References


Chapter 4: An Optimization Framework for Pavement Treatment and Spatio-Temporal Distribution of Work Zone Closures

Abstract

Departments of transportation (DOTs) are responsible for maintaining the roadway network at certain pavement levels and operational performance. While these two metrics are often looked at separately, we developed a framework in a previous study (1), that integrates pavement and operational considerations and allocates for the interaction between them. This paper expands on the developed framework to zoom in into a work zone allocation module that better represents realistic operations and constraints while making decisions at the network level. The focus of this paper is on the development of a systematic and comprehensive methodology to optimize the allocation of networkwide pavement treatment work zones over space and time. We hypothesized that an adjacency function would be highly correlated with the travel time obtained by running a full-scale simulation. The findings indicated that the adjacency computation achieved a high R squared of 0.96, which confirms the hypothesis of the strong relationship between the developed adjacency function and network travel time.
Introduction

Departments of transportation (DOTs) strive to achieve pavement performance outcomes to keep roadway networks in a state of good repair. Yearly budgets are allocated for maintenance and rehabilitation treatments that address pavement needs. Nevertheless, scheduling different pavement treatments across the roadway network results in roadway closures and work zones that would undoubtedly interfere with ordinary traffic operations. On the other hand, DOTs are also responsible for maintaining traffic operational performance. They implement traffic control and traffic demand management strategies that would affect the distribution of traffic across the network. However, these strategies not only affect the levels of congestion and other operational performance metrics, but they also affect the distribution of traffic load across the network, which, in turn, impacts the deterioration of pavement and its performance.

In a previous study (1), we introduced an integrated simulation framework that considers the reciprocal interaction between traffic and pavement. The research presented a proof-of-concept study that proves the range of potential performance improvements that would result from considering both pavement and operations in tandem. Ultimately, the goal is to assist engineers in selecting the traffic operation strategy that would optimize their pavement treatment plans to keep the pavement in a state of good repair while minimizing the overall pavement treatment cost and reducing travel times.

This paper expands on the developed framework in (1) to zoom in on a work zone allocation module that better represents realistic operations and constraints while making decisions at the network level. Improving the representation of traffic operations in the context of the integrated framework is of particular importance, since the project level work zone
distribution over the network, eventually affects the overall system pavement and operational performance, and impacts lifecycle performance and maintenance needs.

The focus of this paper is on the development of a systematic and comprehensive methodology to optimize the allocation of networkwide pavement treatment work zones over space and time. In addition, a surrogate function was developed to reduce the optimization computation burden so that researchers would be able to conduct work zone allocation optimization without having to run expensive simulation work. The surrogate function can also help estimate the work zone operational performance impact (e.g., travel time) when considering alternative work zone closure schedules. The suggested hypothesis is that an adjacency function, developed later in this paper, would alleviate the need to run a full-scale simulation in the optimization step and use the adjacency function instead to help describe network-level travel performance impacts. After optimizing a pavement treatment selection plan, the adjacency function is used to distribute the selected treatments over the number of weeks in the paving period. Aimsun simulations are later performed to compute the travel time impacts of the work zone closure temporal and spatial distributions and test whether there is a strong correlation between the adjacency function and the overall network travel time.

**Background**

The problem of work zone distributions over the network is a significant challenge. Many previous papers investigated reducing the total costs (agency, user, safety, and environmental) related to work zone scheduling (2, 3). However, the scope of these papers is usually at the project level, focusing on a particular project, particular strategies, over a few links in the network, etc. These papers primarily focus on crew scheduling, resource allocations, productivity
and weather constraints, specific traffic controls, and exact start times and durations, among other details (4–6).

On the other hand, other research efforts have been focused on the network-level treatment allocation problem. Typically, these papers consider larger networks and explore long-term pavement performance and life cycle costs (7). In some cases, multi-objective optimizations are considered, and operational performance is accounted for using mathematical model formulations (8).

However, when accounting for the effects of treatment scheduling on traffic loading and, subsequently, the effect of traffic loading on pavement deterioration and scheduling decisions, more detailed inputs on the work zone and project spatial and temporal distribution are required. This is where our adjacency function-based strategy comes in to bridge the gap and offer a compromised consideration of work zone effects on network-level long-term planning projects. The resulting developed system allows for a simulation-based surrogate function to feed into the treatment work zone scheduling optimization.

Virginia DOT (VDOT) current practice

Pavement Management Systems (PMSs), available for every state in the United States, typically encompass two main elements; pavement condition data and decision-making methods (9). VDOT currently determines pavement treatment needs to be based on decision matrices that consider ratings, paving history, roadway categories, conditions, and traffic level. The Critical Condition Index (CCI) is used by VDOT as a pavement performance metric. Its values range between zero and 100, with 100 referring to a total score for perfect pavement conditions. Typical maintenance and rehabilitation treatments vary in aggressiveness. They can be categorized into DN or Do Nothing, PM or Preventive Maintenance, CM or Corrective
Maintenance, RM or Restorative Maintenance, RC or Rehabilitation or Reconstruction, which is the most aggressive and typically requires full reconstruction. These treatment categories also vary in cost and duration. Most importantly, these treatments differ by their ability to restore CCI to a perfect 100 (PM can increase the score by eight at most) and by their impact on future pavement deterioration \cite{10, 11}

VDOT allocates a yearly budget for maintenance and rehabilitation treatments to maintain specific performance targets. The typical paving season ranges from April to December, which is when pavement work must be completed. The weather plays a significant role in the definition of the paving season, where January to March is considered to be the coldest months.

Projects are aggregated into contracts that have comparable value, and that try to group routes to minimize contractors’ mobilization costs. It is typically up to contractors to arrange their schedules as long as they deliver their projects on time.

Our integration framework, with the work zone extension presented in this paper, aims to optimize these treatment allocations, given their impact on traffic operations and future pavement costs.

**Methods**

Integrated Simulation – Optimization Framework

The main idea behind the integrated framework relies on the concept of traffic-pavement interaction \cite{1, 12}. As shown in Figure 19, the interaction between traffic and pavement implications forms a closed loop. The traffic distribution across the network translates into load distribution on the pavement, affecting the pavement condition and deterioration. Deteriorated pavement requires maintenance treatments, which need roadway blockages to perform the
necessary work. The location and schedule of blockages would then affect the traffic distribution across the network and, again, affect the traffic loads.

In our previous work (12), we used a Python-based open-source modeling software package (Pyomo) and a traffic macroscopic/mesoscopic simulator (Aimsun) to implement our framework. The integrated system aimed at maximizing CCI as a measure of pavement performance and reported the impact on travel time as a measure of operational performance. The framework is expanded in this paper to account for travel time as a different objective along with CCI and to present a solution for the simulations of the work zone impacts on traffic using the adjacency function technique.

Pavement Treatment Temporal and Spatial Distribution Planning Process

The optimization framework is used to generate a weekly treatment schedule for the budgeted paving season. The goal is to achieve optimized pavement and operational performance within the allocated budget. For this reason, two optimization problems are created; the first one focuses on selecting the treatment category (DN, PM, CM, to RC) that optimizes CCI and travel
time, whereas the latter is concerned with optimizing spreading the corresponding roadway closures across the weeks for optimum operational performance.

For the overall optimization problem, pavement performance is represented by a CCI maximization, and total travel time minimization represents operational performance. While the closure distribution problem is designed to optimize travel time, travel time is still considered in the treatment selection problem. For that reason, the Bureau of Public Roads (BPR) function developed by the Federal Highway Administration (FHWA) is used to lure the solution in the correct direction. Figure 2 shows the overall optimization process. The figure shows that the network attributes (network graph, capacities, speed, etc.) are combined with the original volume demands and pavement conditions data to optimize the selection of the link treatment types (and determination of which link needs to be treated given the available budget). A simulation performed in Aimsun generates the traffic distribution for the network, where no closures are applied, that go into the treatment selection optimization. The optimizer then uses this traffic volume information, along with pavement condition data, to assess pavement performance and deterioration and accordingly select the pavement treatments. The results of this optimization step also determine the overall pavement performance metric (total CCI).

Next, a new problem is defined (closure distribution optimization) to distribute the treatment schedule over time. To complete this step, information about network paths used frequently by traffic is used along with the adjacency function to minimize the impact of closures during each week. The adjacency function assumes that once an upstream link is closed, there is a minimal impact of closing other links on the same path that are in close proximity, as opposed to closing other links that would increase congestion of a different set of traffic. The outcome of this step of the process is the generation of the closure distribution on a weekly basis.
To test the hypothesis that the adjacency function could be used in lieu of a full-scale simulation, each closure distribution scenario corresponding to a particular week is simulated in Aimsun to test the overall network travel time correlation with the adjacency function. Equivalent capacity reductions caused by work zone distributions over the network are used to reduce corresponding link capacities in Aimsun. Aimsun is then run to generate the new travel time and volume distribution data. The overall travel time for the network is obtained after running the entire set of scenarios.
Figure 20. Treatment Spatial and Temporal Distribution Planning Process
Treatment Selection Optimization

As mentioned earlier, this optimization problem aims at providing the optimal treatment category selection across the network.

Given L links across the considered roadway network and I treatment categories (0:DN, 1:PM, 2:CM, 3: RM, 4:RC). The problems formulate as follows:

**Decision Variable:**

\( x_{il} \): binary decision variable equal to 1 if treatment \( i (i \in I) \) is applied to link \( l (l \in L) \) and 0 otherwise

**Constraints:**

CCI\(_l\) constraint represents the deteriorated value of CCI by the end of the analysis period.

CCI\(_l\) deterioration is based on a developed model which accounts for the effect of traffic volume on pavement deterioration.

\[
CCI_l = \sum_i x_{il} \times [CCl_0 - \exp(a_i - b_i \times c_i \times \ln(\frac{v}{t}) - d_i \times v_i)] \forall l
\]

Where

\( a_i, b_i, c_i, d_i, \) and \( e_i \): treatment specific deterioration coefficients

\( CCl_0 \): CCI immediately after treatment

\( t \): Years since last treatment activity

\( v \): AADT

CCI definition constraint: \( CCI_l \leq 100 \forall l \)

Budget constraint: \( \sum_l \sum_i x_{il} \times c_{oi} \times l_{e_l} \times \ln l \leq B \)

Where

\( c_{oi} \): cost ($ per lane mile) of applying treatment \( i (i \in I) \)

\( l_{e_l} \): length of link \( l (l \in L) \)
ln_l: number of lanes of link l (l∈L)

B: budget

One treatment per link constraint: Σ_l x_{il} = 1 ∀l

**Objective Functions:**

Objective 1(Obj1): Maximize the sum of CCI: Max Σ_l CCI_l * le_l * ln_l

Objective 2(Obj2): Minimize the sum of Travel Time (TT): Σ_l T_{0l} (1 + 0.15 \frac{V_{l}^4}{C_{l}})

Where

T_{0l}: link free flow speed

C_{l}: link capacity

The two objectives are then normalized and weighted into a single objective function:

Maximize Z = W_{Obj1} \cdot \frac{Obj1-Obj1_{min}}{Obj1_{max}-Obj1_{min}} + W_{Obj2} \cdot \frac{Obj2-Obj2_{min}}{Obj2_{max}-Obj2_{min}}

Where

W_{Obj1}, W_{Obj2}: weights of Obj1 and Obj2, respectively

W_{Obj2} = 1 - W_{Obj1} (given only 2 objectives)

Obj1_{max}, Obj1_{min}, Obj2_{max}, Obj2_{min}: are computed by considering the maximization and minimization of each separate objective.

The problem is python coded into Pyomo framework (13, 14), which generated the treatment selection plan.

**Adjacency Function Definition**

An adjacency function is defined and used as the objective function for the closure scheduling problem. The adjacency function aims at reflecting the relative effect that different combinations of blockages have on traffic. The idea is that roadway sections belonging to the
same path carry “similar” traffic volumes, and thus, added effect of closing additional links on a path is minimal (Figure 21 illustration using money coins, similar along a path).

In addition, it is assumed that roadway sections belonging to the same path have reduced effects when they are closer to each other. Besides, the further upstream is the section on the path, the more its effect on traffic. As such, for a certain path in the network, each roadway segment is assigned a weight based on its position along the path. The link further upstream will have the highest weight (equal to the number of links along the path), and then a 1-point weight is subtracted for each position downstream; the most downstream link is assigned a weight of 1. Figure 22 illustrates an example of weight allocation along a path.
The adjacency function is computed for every week and every path based on the links selected to receive treatment during a particular week (closure distribution optimization problem). The function subtracts the weight of every selected link from the weight of the most upstream link along the path. For instance, if a path is composed of links A, B, C, D, and E (upstream to downstream), and in a particular scenario 1, links B, C, and E are selected for closure, the computations for the adjacency function will go as follows:

1) Computation of weights:

Weight A=5
Weight B=4
Weight C=3
Weight D=2
Weight E=1
2) Computation of adjacency with B, C, and E being selected for closure:

Weight of most upstream link selected=Weight B=4

Adjacency=4+(4-Weight C)+(4-Weight E)=4+(4-3)+(4-2)=4+1+2=7

On the other hand, in scenario 2, if links A, C, and E are selected:

1) Computation of weights: (same as previous)

2) Computation of adjacency with A, C, and E being selected for closure:

Weight of most upstream link selected=Weight A=5

Adjacency= 5+(5-Weight C)+(5-Weight E)=5+(5-3)+(5-2)=5+2+3=10

The second scenario resulted in a higher adjacency, which is expected with A being farther away from C and E and also being farther upstream.

Finally, besides the anticipated reduced effect on operational performance and total travel time, a primary benefit of keeping concurrently treated sections adjacent is the ease it brings to crew mobilization. To account for the congestion effects on link closures, the adjacency function is multiplied by the volume-to-capacity ratio (V/C ratio) of the most upstream blocked link. The adjacency is defined for every path for every week.

Closure Distribution Optimization

Following the assignment of the location and type of treatments in the treatment selection optimization problem, their weekly temporal distribution is optimized in this closure distribution optimization. The optimization is based on the adjacency function developed earlier. The goal is to minimize the summation of all adjacency functions pertaining to all weeks under consideration (set W) summed up over the set of paths P. The problem can then be mathematically formulated as follows:
**Decision Variable:**

\(x_{lw}\): binary decision variable equal to 1 if link \(l \in L\) is receiving treatment in week \(w \in W\) and 0 otherwise

**Constraint:**

Most upstream link receiving treatment definition constraint:

\(l_{upw} = 1\) where \(\forall p \in P, \forall w \in W, l\) corresponds to \(l\) of \(\max(x_{lw} \cdot w_{lp})\)

**Objective:**

Minimize sum of Adj:

\[
\text{Min } \sum_{w} \sum_{p} \text{Adj}_{pw} = \text{Min } \sum_{w} \sum_{p} [\left(\frac{V}{C}\right)_{l_{upw}} \cdot (w_{lp} \cdot \sum_{l \in p}(w_{lp} - x_{lw} \cdot w_{lp}))]
\]

Where

- \(w_{lp}\): weight of link \(l \in (p \in P)\)
- \(\left(\frac{V}{C}\right)_{l_{upw}}\): volume to capacity ratio of link \(l_{upw}\) corresponding to a link \(l \in L\)

A genetic algorithm (GA) is used to solve this closure distribution optimization problem. The problem was python coded into the Pymoo framework (15), which solves the GA problem. A population size of 100 and a generation size of 150 were used to generate the solution.

**Aimsun Simulation**

Aimsun simulation software is used to conduct large-scale hybrid macro/meso traffic simulations in a computationally acceptable timeframe. Aimsun produces system travel times and traffic volumes on different routes based on the selected road closure strategy. The application of the treatment plan on the network is achieved by reducing the capacity of the affected links using software Application Programming Interface (API) and Python scripting.
The resulting reduced capacities in the Aimsun simulation affect traffic distribution and system performance expectations for the next evaluation period.

**Case Study**

In this section, we apply the optimization framework to the same case study used in our previous paper (12). This network in Northern Virginia (Figure 23) was selected due to the high traffic level and the possibility of the application of different traffic control and management strategies. However, in this case study, the focus was on the application of the framework, which necessitated the extraction of information related to vehicle paths and characteristics.

Aimsun hybrid macro/meso simulation was performed for the selected freeway and major arterials on the network. The red delineated area (simulation area) is the one considered for mesoscopic simulation, where all the analysis was focused. The path information extracted from Aimsun is shown in Figure 24, while the paths themselves are shown in Figure 25.

*Figure 23. Study Area*
Results

The outcome of the treatment selection optimization is shown in Figure 26. It shows which links are receiving which type of treatment over the planning period horizon. Mostly PM and CM treatments were selected. These treatments resulted in a CCI increase from an average of 73 to an average of 96.
Figure 26. Optimized treatment plan

Pymoo genetic algorithm was run to solve the closure distribution optimization. Figure 27 shows the convergence of the solutions over the generations of the GA. No further significant improvement was achieved over the last iterations.

Figure 27. Convergence of Pymoo GA iteration solutions

Aimsun Simulations were performed for each scenario (a) through (t) shown in Figure 28. The red links correspond to the location of the blocked links during each scenario.
The total travel times corresponding to each scenario were recorded and then, using Jump (JMP) software, were fitted against the adjacency function components for every week. The results of the actual vs. predicted plot are shown in Figure 29. Considered components included: the total adjacency function per week, the total length of links closed during a week, the number

Figure 28. Weekly Closures Schedule

(a)-(t): Closures corresponding to each week
of paths blocked, and the average and maximum V/C values of the upstream link that were used in the adjacency computation for the different paths for each week.

![Figure 29. Total Travel Time Actual vs. Predicted Plot](image)

In addition, dynamic profilers were constructed to provide further insight into the relationship between travel time and the different considered factors (Figure 30).

![Figure 30. Dynamic Profilers](image)

(a): Max V/C<0.75

(b): Max V/C=0.75
Discussion

The following main points were observed in the results:

- The outcomes of the simulation showed treatments that only include PM and CM. The considered area had a relatively high average CCI.
- The GA showed a good convergence.
- Within each week, links closer together on every path were selected, which reflects the concept behind the adjacency formulation.
- The actual vs. predicted plot provided a high R squared of 0.96, which confirms the hypothesis of a strong relationship between the developed adjacency function and network travel time.
- For a maximum V/C lower than 0.75, travel time seemed to be directly proportional to the increase in adjacency. The higher the adjacency, the higher the travel time experienced across the network. This was apparent by moving the maximum V/C ratio to the right in the profiler.
- The total length of the closed path links seemed to have an inverse effect on travel time, which proved the efficiency of the selection. Once a path or road is blocked, it does not matter how much distance is blocked (bottleneck effect).
• It was hypothesized that when the maximum V/C ratio on the path links was above 0.75 (which might indicate that some of the links reached the congested regime), the adjacency started having a negative effect on travel time as it increased, resulting in a decrease in network travel time.

• Some results might appear counterintuitive, such as the inverse relationship between the average V/C ratio and travel time. These results might be due to the fact that the average V/C and the maximum V/C ratio are highly correlated. These outcomes might also be attributed to a reduced number of vehicles entering the network at high congestion levels and to the attainment of the congested regime within the network.

Conclusions

This study addressed the problem of determining and distributing work zones on the network to minimize total travel time and improve performance efficiency in the optimization process. In this study, we hypothesized that an adjacency function would be highly correlated with the travel time obtained by running a full-scale simulation. The findings indicated that the adjacency computation achieved a high R squared of 0.96, confirming the strong relationship between the developed adjacency function and network travel time. This paper addresses an important issue left unanswered and provides solutions to the problem of integrating pavement and operational performance while addressing the spatial and temporal work zone distribution.
References


Chapter 5: Encapsulation of the Simulation Optimization Process Using Machine Learning

In an effort to offer the end user a low computation latency, we developed a user-friendly decision-support tool that assists in the pavement treatment and project selection planning process. We use machine learning models to encapsulate the simulation optimization process. Machine learning models were trained to offer the user a recommended treatment plan for a set of input conditions. This allows the user to conduct sensitivity analysis to predict treatment plan recommendations based on changes in traffic volume input.

This chapter focuses on demonstrating the process through the variation of specific input parameters and studying their subsequent effect on treatment needs. For that purpose, we created hypothetical scenarios of additional demand on the transportation network. The additional volume of traffic was injected along five selected paths using dummy nodes (Figure 31). These hypothetical scenarios represent additional volumes generated due to future developments and represent suggestions for traffic routings as a traffic control strategy when facing extra demand on the network.

Figure 31. Paths Enduring Additional Traffic Demand
The design of experiments was conducted in JMP software to create a wide range of hypothetical scenarios of combinations of extra volumes along the selected paths (Figure 32). These scenarios and their outputs were used to train the machine learning models.

![Design of Experiments in JMP](image)

**Figure 32. Design of Experiments in JMP**

For each scenario combination of (additional) volumes, simulations were conducted in Aimsun software to determine the resulting distribution of traffic volumes across the transportation network. The outputs from Aimsun were then input into the treatment selection optimization and the resulting treatments were recorded. The volume variation input scenarios and the resulting treatments were then uploaded to Azure Machine Learning database for use in training models.

Microsoft Azure provides a cloud web-based computing service that facilitates the development of machine learning models without the need for installed software and large
computer power. The trained model could then be called through a web service that is connected to the cloud storage database. In essence, the trained machine learning model will be able to replace the optimization and simulations in our framework and simply provide the required solution given a specific input.

The flow graph created for the training experiment in Azure used the sample data resulting from our Simulations-Optimizations. The data was then split 80/20 for training and testing, and a multiclass neural network model was trained and evaluated (Figure 33).

![Microsoft Machine Learning Studio](image)

**Figure 33. Training Experiment in Azure Machine Learning Studio**

Finally, the experiment was deployed as a web service and consumed in Microsoft Excel to provide a user-friendly decision support tool for treatment prediction. The input and output interface is shown in Figure 34.
In this chapter, we demonstrated the process of encapsulating the simulation-optimization framework into machine learning models, from creating the database to training and visualization in Excel (Figure 35). In the future, the database and the decision support tool will be expanded to include additional parameters.

Figure 34. Decision Support Tool Input and Output

Figure 35. From Simulation to Visualization
Chapter 6: Conclusions and Future Work

This dissertation focused on the interaction between the fields of pavement and operational performance within the transportation area. The research starts by developing the integrated framework (Chapter 2), applies it to a particular TDM strategy application in Chapter 3, and refines it with a work zone consideration expansion in Chapter 4.

Chapter 2 introduced the developed framework that integrates traffic demand and traffic operation strategies with pavement condition assessment and treatment optimization. A CCI prediction model was modified to account for the proposed integrated framework. The Aimsun simulation tool was used to conduct a simulation of a case study network to produce (1) Total travel time performance metric and (2) Modified traffic volume distributions on the transportation network. An optimizer was used to determine the optimum pavement treatment for a given budget, resulting in new scheduled work zones and associated reduced capacities on the selected treatment road segments. This information was fed into the Aimsun simulation to assess the impact of the changes in capacities on the volume distribution for the next time step.

The proposed framework was applied to a proof-of-concept study in Northern Virginia. The outputs of the case study displayed ranges of possible improvements in CCI values across the network along with the associated impacts on the total travel time. Preliminary analysis showed that the optimized model could achieve a maximum CCI increase from an average of 65 to 100, causing a travel time increase of about 80%. On the other hand, a do-nothing approach will preserve travel time but cause an average CCI decrease of 7 points during one fiscal year.

Chapter 3 presented the first step towards pavement performance consideration in the presence of tolled facilities. In this chapter, I studied the specific site around I-66 inside the beltway, which newly applied dynamic tolls during the AM and PM peak hours. The integrated
traffic-pavement framework was applied to address both the operational and pavement performance of the network. Aimsun hybrid macro/meso dynamic user equilibrium experiments were used to simulate the network with the modified cost function taking care of the dynamic pricing along the I-66 tolled facility.

The results of the simulations of the selected network with and without the application of tolls demonstrated the difference in congestion distribution under the two scenarios. This highlighted the importance of considering traffic load distribution when deciding on a pavement treatment and rehabilitation plan budget allocation. The results from the tested scenarios showed how far off pavement performance could fall if the treatment plan was not strategically developed. It is crucial that the pavement treatment and rehabilitation plan be tailored to the specific case in hand, which is where the role of our developed optimization framework comes into play.

Afterward, in Chapter 4, the research addressed the problem of determining and distributing work zones on the network to minimize total travel time and improve performance efficiency in the optimization process. In this chapter, I hypothesized that an adjacency function would be highly correlated with the travel time obtained by running a full-scale simulation. The findings indicated that the adjacency computation achieved a high R squared of 0.96, confirming the strong relationship between the developed adjacency function and network travel time. This dissertation chapter addresses an important issue left unanswered and provides solutions to the problem of integrating pavement and operational performance while addressing the spatial and temporal work zone distribution.

Finally, in Chapter 5, we demonstrated the process of encapsulating the simulation-optimization framework into machine learning models. Using these trained models, we
developed a user-friendly decision-support tool that assists in the pavement treatment and project selection planning process.

The developed framework could be tailored to target specific objectives within the possible range of improvements based on the site-specific requirements. This work opens the door to a vast area of research within the nexus of the fields of system operations and pavement management.

Future work could implement and assess the impact of the proposed methodology on real sites in different areas. It could also test the framework within the context of various proposed traffic demand and traffic control strategies or future developments specific to the study areas. Future research would expand on the integrated framework to account for other performance metrics (e.g., safety, environment, etc.). In addition, researchers could investigate expanding the deterioration model to account for the entire traffic load spectra using the MEPDG methodology (Mechanical-Empirical Pavement Design Guide). It is also possible for future research to expand on the treatment selection optimization problem to include additional constraints related to the adjacency of similar treatment categories, crew and resource availability, or any additional site and DOT-specific constraints. Ultimately, additional framework expansions and case study scenarios and results should feed into (1) growing a shared database and into (2) developing, training, and growing the developed tool into a universal, easily accessible decision support tool that would assist engineers and DOTs in decision making and relief the financial and technical burden that go into pavement and traffic management planning.