CIAMTIS

U.S. DOT Region 3 University Transportation Center

CIAMTIS Lehigh Research Experience for Undergraduates (REU) Program

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16. Abstract Lehigh University, through its Institute for Cyber Physical Infrastructure and Energy (I-CPIE) and its Advanced Technology for Large Structural Systems (ATLSS) Engineering Research Center, in conjunction with the Pennsylvania Infrastructure Technology Alliance (PITA) program, conducted a virtual 10-week CIAMTIS Lehigh Research Experience for Undergraduates (REU) program. The program, which ran from May 27, 2020 through July 31, 2020, featured Lehigh University students who participated in a virtual program that exposed the students to a well-rounded experience, including both research-focused and professional development-focused activities. The program's activities included professional skills development workshops in addition to the assignment of students to an active CIAMTIS research project at ATLSS or a technical project related to the mission of CIAMTIS under the direction of the project Principal Investigator and graduate student mentor to help them navigate through the research project experience. The program culminated with a final report, presentation, and poster on their research findings.			
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CHAPTER 1

Introduction

BACKGROUND

Lehigh University, through its Institute for Cyber Physical Infrastructure and Energy (I-CPIE) and its Advanced Technology for Large Structural Systems (ATLSS) Engineering Research Center, in conjunction with the Pennsylvania Infrastructure Technology Alliance (PITA) program, conducted a 10-week CIAMTIS Lehigh Research Experience for Undergraduates (REU) program. The program, which was conducted entirely virtually due to COVID-19, ran from May 27, 2020 through July 31, 2020. Lehigh University undergraduate students participated in the research-centric program, which exposed the students to a well-rounded professional development experience. Students were assigned to an active CIAMTIS research project at ATLSS or a research project that fit within the mission of CIAMTIS under the direction of the project Principal Investigator and graduate student mentor to help them navigate through the research project experience. Additionally, program activities included professional skills development workshops and trainings. The program culminated with a final report, presentation, and poster on their research findings.

OBJECTIVES

The objective of the REU program is to provide the students with a well-rounded professional development experience, featuring research as part of an active CIAMTIS research project at Lehigh University or a research project that fits withn the mission of CIAMTIS, and also including professional skills development workshops and seminars. This program exposed the students to research areas important to CIAMTIS while providing the students with research and professional development training that will prepare the students for future professional endeavors.

DATA AND DATA STRUCTURES

The participating students developed final reports, presentations, and posters. Copies of the final reports are included within Appendix A of this final report.

CHAPTER 2

Methodology

INTRODUCTION

The REU program was conducted under the following criteria:

1. CIAMTIS Lehigh project principal investigators identified candidate students to participate in the Summer 2020 CIAMTIS Lehigh REU program. Additionally, an announcement regarding the program opportunities was distributed to Lehigh University undergraduate Civil and Environmental Engineering students for program consideration.

2. Recommendations and resumes were reviewed and interviews conducted, as necessary, in order to identify a candidate student for each active CIAMTIS Lehigh research project.

3. REU program dates were finalized as May 27, 2020 – July 31, 2020.

4. Students identified for the program were notified of their selection.

5. Principal Investigators and graduate student mentors were finalized for each project.

7. Program workshops and seminars were identified and scheduled.

8. Operation of the CIAMTIS Lehigh REU program, including workshops and project research, took place under the direction of the project Principal Investigator and project mentors.

9. Program participants completed final reports, posters, and formal presentations at the conclusion of the program.

CHAPTER 3

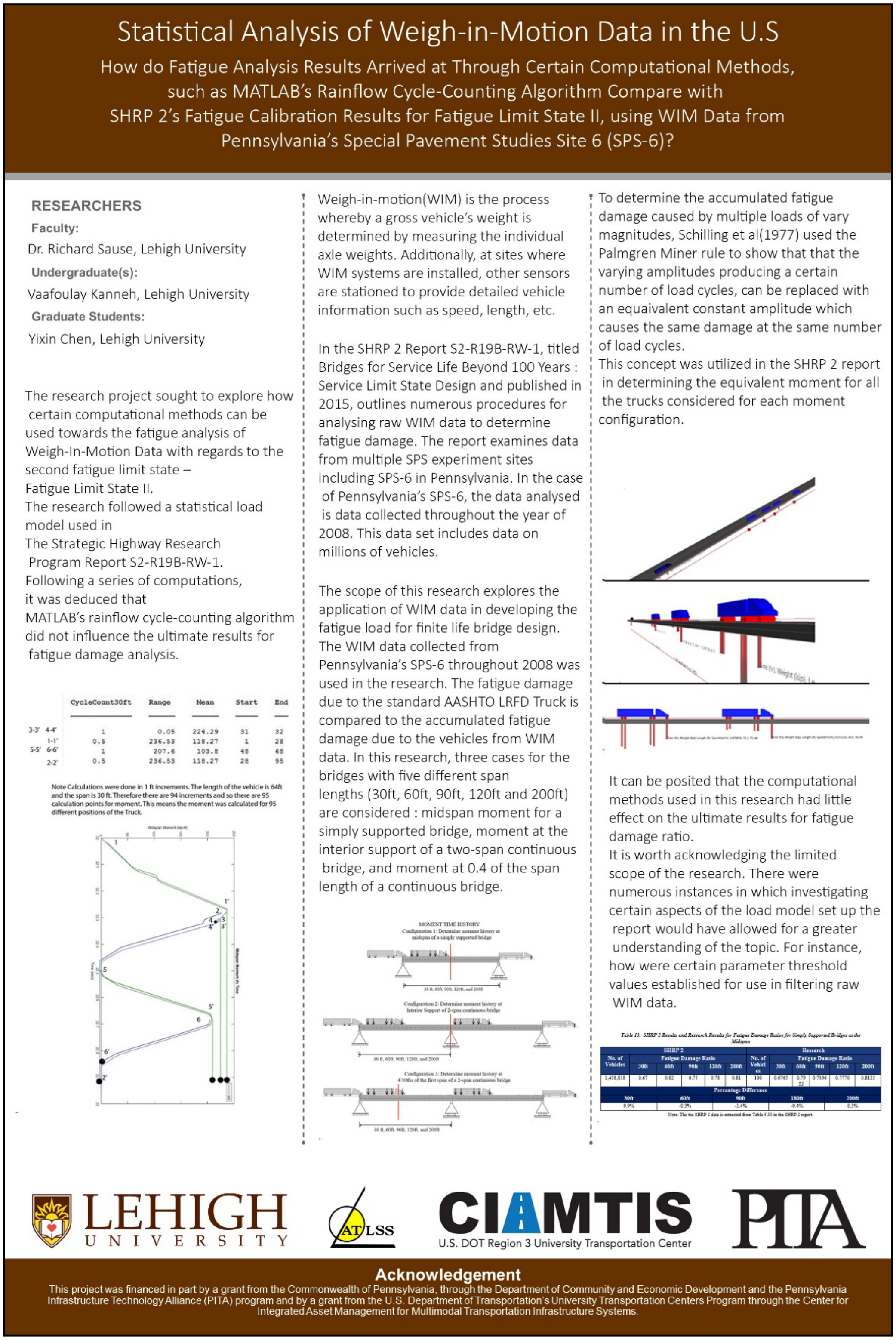
Findings

The project matrix, along with particpating students, for the virtual CIAMTIS Lehigh REU program is presented in Table 1. Participating students are shown in Figure 1 in front of the ATLSS Engineering Research Center at Lehigh University. Each student conducted research on a project under the direction of a PI and project mentor. The results of this research were summarized in final project reports, which accompany this report in Appendix A, along with final posters, which are shown in Figures 2-7. Each student made a final program presentation to the project PIs prior to the conclusion of the program.

Table 1. Project, student, university, PI and mentor matrix for the CIAMTIS Lehigh REU program.

CIAMTIS Project Title	REU Student	University	PI	Mentor
Statistical Analysis on Weight-in-Motion Data Measured in the U.S.	Vaafoulay Kanneh	Lehigh University	Richard Sause	Yixin Chen
Fatigue Life Estimation of Bridges with Smart Mobile Sensing	Jack Heller	Lehigh University	Shamim Pakzad / Martin Takac	Martin Takac
Efficient Service Life Extension of Bridges through Risk-based Life-cycle Management and High-performance Construction Materials: Emphasis on Corrosion-resistant Steel	Trystan Golden	Lehigh University	Dan Frangopol / David Yang	David Yang
Road Pavement Condition Monitoring by Embedded Crowdsensing	Maximillian Machado	Lehigh University	Liang Cheng	Charles Inwald
Smart Mobile Platform for Model Updating and Life Cycle Assessment of Bridges	Rachel Hamburger	Lehigh University	Shamim Pakzad/ Martin Takac	Helen Whalen; Soheila Sadeghi Eshkevari
Assessment of Fatigue Cracks Initiating at the Root of Fillet Welds in Steel Orthotropic Bridge Decks	Colin Lerner	Lehigh University	Richard Sause	Ian Hodgson

Figure 1. CIAMTIS Lehigh REU students. Top row, from left to right: Vaafoulay Kanneh, Jack Heller, and Trystan Golden. Bottom row, from left to right: Maximillian Machado, Rachel Hamburger, and Colin Lerner.



Statistical Analysis of Weigh-in-Motion Data in the U.S

How do Fatigue Analysis Results Arrived at Through Certain Computational Methods, such as MATLAB's Rainflow Cycle-Counting Algorithm Compare with SHRP 2's Fatigue Calibration Results for Fatigue Limit State II, using WIM Data from Pennsylvania's Special Pavement Studies Site 6 (SPS-6)?

RESEARCHERS

Faculty:

Dr. Richard Sause, Lehigh University

Undergraduate(s):

Vaafoulay Kanneh, Lehigh University

Graduate Students:

Yixin Chen, Lehigh University

The research project sought to explore how certain computational methods can be used towards the fatigue analysis of Weigh-In-Motion Data with regards to the second fatigue limit state – Fatigue Limit State II.
The research followed a statistical load model used in The Strategic Highway Research Program Report S2-R19B-RW-1.
Following a series of computations, it was deduced that MATLAB's rainflow cycle-counting algorithm did not influence the ultimate results for fatigue damage analysis.

	CycleCount30ft	Range	Mean	Start	End
3-3' 4-4'	1	0.05	224.29	31	32
1-1'	0.5	236.53	118.27	1	28
5-5' 6-6'	1	207.6	103.8	48	68
2-2'	0.5	236.53	118.27	28	95

Note Calculations were done in 1 ft increments. The length of the vehicle is 64ft and the span is 30 ft. Therefore there are 94 increments and so there are 95 calculation points for moment. This means the moment was calculated for 95 different positions of the Truck.

Weigh-in-motion(WIM) is the process whereby a gross vehicle's weight is determined by measuring the individual axle weights. Additionally, at sites where WIM systems are installed, other sensors are stationed to provide detailed vehicle information such as speed, length, etc.

In the SHRP 2 Report S2-R19B-RW-1, titled Bridges for Service Life Beyond 100 Years : Service Limit State Design and published in 2015, outlines numerous procedures for analysing raw WIM data to determine fatigue damage. The report examines data from multiple SPS experiment sites including SPS-6 in Pennsylvania. In the case of Pennsylvania's SPS-6, the data analysed is data collected throughout the year of 2008. This data set includes data on millions of vehicles.

The scope of this research explores the application of WIM data in developing the fatigue load for finite life bridge design. The WIM data collected from Pennsylvania's SPS-6 throughout 2008 was used in the research. The fatigue damage due to the standard AASHTO LRFD Truck is compared to the accumulated fatigue damage due to the vehicles from WIM data. In this research, three cases for the bridges with five different span lengths (30ft, 60ft, 90ft, 120ft and 200ft) are considered : midspan moment for a simply supported bridge, moment at the interior support of a two-span continuous bridge, and moment at 0.4 of the span length of a continuous bridge.

To determine the accumulated fatigue damage caused by multiple loads of vary magnitudes, Schilling et al(1977) used the Palmgren Miner rule to show that that the varying amplitudes producing a certain number of load cycles, can be replaced with an equaivalent constant amplitude which causes the same damage at the same number of load cycles.
This concept was utilized in the SHRP 2 report in determining the equivalent moment for all the trucks considered for each moment configuration.

It can be posited that the computational methods used in this research had little effect on the ultimate results for fatigue damage ratio.
It is worth acknowledging the limited scope of the research. There were numerous instances in which investigating certain aspects of the load model set up the report would have allowed for a greater understanding of the topic. For instance, how were certain parameter threshold values established for use in filtering raw WIM data.

Table 13. SHRP 2 Results and Research Results for Fatigue Damage Ratios for Simply Supported Bridges at the Midspan

SHRP 2						Research					
No. of Vehicles	Fatigue Damage Ratio					No. of Vehicles	Fatigue Damage Ratio				
	30ft	60ft	90ft	120ft	200ft		30ft	60ft	90ft	120ft	200ft
1,458,818	0.67	0.82	0.75	0.78	0.81	100	0.6765	0.7953	0.7396	0.7770	0.8123

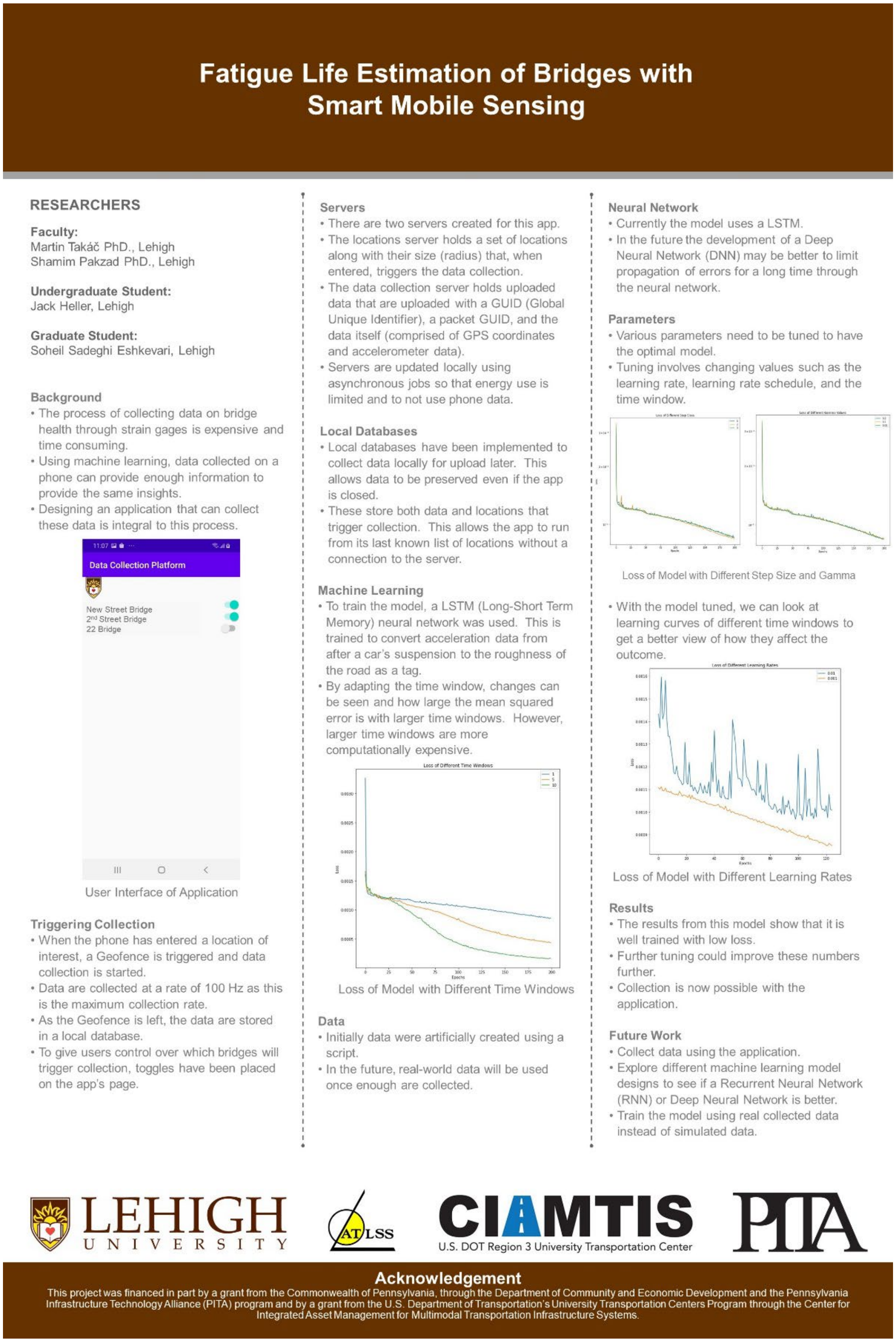
Percentage Difference				
30ft	60ft	90ft	180ft	200ft
0.9%	-0.3%	-1.4%	-0.4%	0.3%

Note: The the SHRP 2 data is extracted from Table 5.30 in the SHRP 2 report.

Acknowledgement

This project was financed in part by a grant from the Commonwealth of Pennsylvania, through the Department of Community and Economic Development and the Pennsylvania Infrastructure Technology Alliance (PITA) program and by a grant from the U.S. Department of Transportation's University Transportation Centers Program through the Center for Integrated Asset Management for Multimodal Transportation Infrastructure Systems.

Figure 2. Project poster for CIAMTIS project entitled *Statistical Analysis on Weight-in-Motion Data Measured in the U.S.*



Fatigue Life Estimation of Bridges with Smart Mobile Sensing

RESEARCHERS

Faculty:
Martin Takáč PhD., Lehigh
Shamim Pakzad PhD., Lehigh

Undergraduate Student:
Jack Heller, Lehigh

Graduate Student:
Soheil Sadeghi Eshkevari, Lehigh

Background

- The process of collecting data on bridge health through strain gages is expensive and time consuming.
- Using machine learning, data collected on a phone can provide enough information to provide the same insights.
- Designing an application that can collect these data is integral to this process.

User Interface of Application

Triggering Collection

- When the phone has entered a location of interest, a Geofence is triggered and data collection is started.
- Data are collected at a rate of 100 Hz as this is the maximum collection rate.
- As the Geofence is left, the data are stored in a local database.
- To give users control over which bridges will trigger collection, toggles have been placed on the app's page.

Servers

- There are two servers created for this app.
- The locations server holds a set of locations along with their size (radius) that, when entered, triggers the data collection.
- The data collection server holds uploaded data that are uploaded with a GUID (Global Unique Identifier), a packet GUID, and the data itself (comprised of GPS coordinates and accelerometer data).
- Servers are updated locally using asynchronous jobs so that energy use is limited and to not use phone data.

Local Databases

- Local databases have been implemented to collect data locally for upload later. This allows data to be preserved even if the app is closed.
- These store both data and locations that trigger collection. This allows the app to run from its last known list of locations without a connection to the server.

Machine Learning

- To train the model, a LSTM (Long-Short Term Memory) neural network was used. This is trained to convert acceleration data from after a car's suspension to the roughness of the road as a tag.
- By adapting the time window, changes can be seen and how large the mean squared error is with larger time windows. However, larger time windows are more computationally expensive.

Loss of Model with Different Time Windows

Data

- Initially data were artificially created using a script.
- In the future, real-world data will be used once enough are collected.

Neural Network

- Currently the model uses a LSTM.
- In the future the development of a Deep Neural Network (DNN) may be better to limit propagation of errors for a long time through the neural network.

Parameters

- Various parameters need to be tuned to have the optimal model.
- Tuning involves changing values such as the learning rate, learning rate schedule, and the time window.

Loss of Model with Different Step Size and Gamma

- With the model tuned, we can look at learning curves of different time windows to get a better view of how they affect the outcome.

Loss of Model with Different Learning Rates

Results

- The results from this model show that it is well trained with low loss.
- Further tuning could improve these numbers further.
- Collection is now possible with the application.

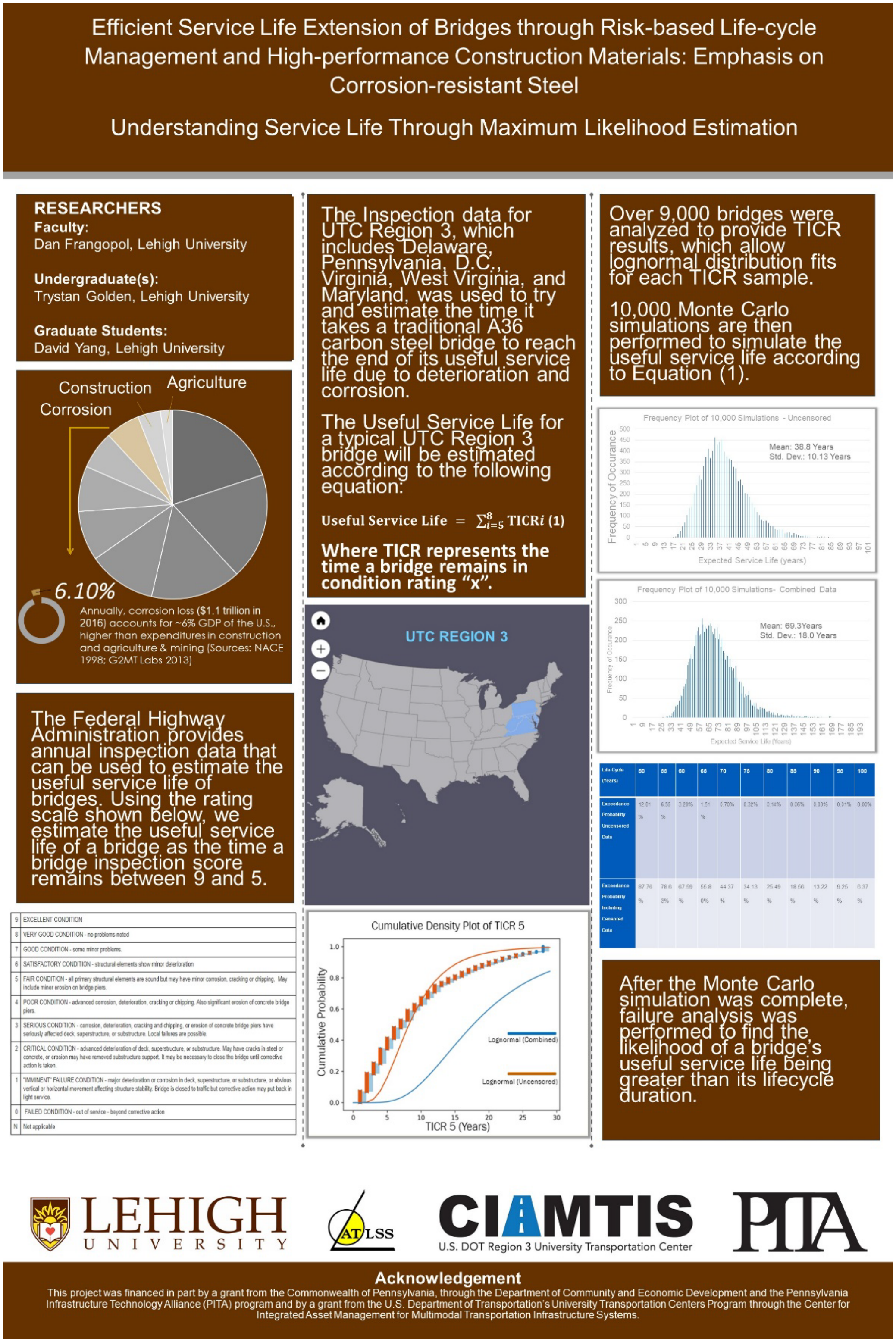
Future Work

- Collect data using the application.
- Explore different machine learning model designs to see if a Recurrent Neural Network (RNN) or Deep Neural Network is better.
- Train the model using real collected data instead of simulated data.

Acknowledgement

This project was financed in part by a grant from the Commonwealth of Pennsylvania, through the Department of Community and Economic Development and the Pennsylvania Infrastructure Technology Alliance (PITA) program and by a grant from the U.S. Department of Transportation's University Transportation Centers Program through the Center for Integrated Asset Management for Multimodal Transportation Infrastructure Systems.

Figure 3. Project poster for CIAMTIS project entitled *Fatigue Life Estimation of Bridges with Smart Mobile Sensing*.



Efficient Service Life Extension of Bridges through Risk-based Life-cycle Management and High-performance Construction Materials: Emphasis on Corrosion-resistant Steel

Understanding Service Life Through Maximum Likelihood Estimation

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6.10%

Annually, corrosion loss ($1.1 trillion in 2016) accounts for ~6% GDP of the U.S., higher than expenditures in construction and agriculture & mining (Sources: NACE 1998; G2MT Labs 2013)

The Federal Highway Administration provides annual inspection data that can be used to estimate the useful service life of bridges. Using the rating scale shown below, we estimate the useful service life of a bridge as the time a bridge inspection score remains between 9 and 5.

9	EXCELLENT CONDITION
8	VERY GOOD CONDITION - no problems noted
7	GOOD CONDITION - some minor problems.
6	SATISFACTORY CONDITION - structural elements show minor deterioration
5	FAIR CONDITION - all primary structural elements are sound but may have minor corrosion, cracking or chipping. May include minor erosion on bridge piers.
4	POOR CONDITION - advanced corrosion, deterioration, cracking or chipping. Also significant erosion of concrete bridge piers.
3	SERIOUS CONDITION - corrosion, deterioration, cracking and chipping, or erosion of concrete bridge piers have seriously affected deck, superstructure, or substructure. Local failures are possible.
2	CRITICAL CONDITION - advanced deterioration of deck, superstructure, or substructure. May have cracks in steel or concrete, or erosion may have removed substructure support. It may be necessary to close the bridge until corrective action is taken.
1	"IMMINENT" FAILURE CONDITION - major deterioration or corrosion in deck, superstructure, or substructure, or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put back in light service.
0	FAILED CONDITION - out of service - beyond corrective action
N	Not applicable

The Inspection data for UTC Region 3, which includes Delaware, Pennsylvania, D.C., Virginia, West Virginia, and Maryland, was used to try and estimate the time it takes a traditional A36 carbon steel bridge to reach the end of its useful service life due to deterioration and corrosion.

The Useful Service Life for a typical UTC Region 3 bridge will be estimated according to the following equation:

$$\text{Useful Service Life} = \sum_{i=5}^{8} \text{TICR}i \ (1)$$

Where TICR represents the time a bridge remains in condition rating "x".

Over 9,000 bridges were analyzed to provide TICR results, which allow lognormal distribution fits for each TICR sample.

10,000 Monte Carlo simulations are then performed to simulate the useful service life according to Equation (1).

Life Cycle (Years)	50	55	60	65	70	75	80	85	90	95	100
Exceedance Probability Uncensored Data	12.81%	6.55%	3.20%	1.51%	0.70%	0.32%	0.14%	0.06%	0.03%	0.01%	0.00%
Exceedance Probability Including Censored Data	87.76%	78.63%	67.59%	55.80%	44.37%	34.13%	25.49%	18.56%	13.22%	9.25%	6.37%

After the Monte Carlo simulation was complete, failure analysis was performed to find the likelihood of a bridge's useful service life being greater than its lifecycle duration.

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This project was financed in part by a grant from the Commonwealth of Pennsylvania, through the Department of Community and Economic Development and the Pennsylvania Infrastructure Technology Alliance (PITA) program and by a grant from the U.S. Department of Transportation's University Transportation Centers Program through the Center for Integrated Asset Management for Multimodal Transportation Infrastructure Systems.

Figure 4. Project poster for CIAMTIS project entitled *Efficient Service Life Extension of Bridges through Risk-based Life-cycle Management and High-performance Construction Materials: Emphasis on Corrosion-resistant Steel*.

Road Pavement Condition Monitoring by Embedded Crowdsensing: Incentive Mechanism Analysis

RESEARCHERS

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- BACKGROUND

As road infrastructure continues to increase in size and complexity, new and innovative solutions must be developed to cope with road degradation. Current methods used to collect road condition information do not mitigate the stress in covering 4.18 million miles of road in the United States (Russell, 2017). One viable solution is to create a crowdsensing network of smart phones and utilize the embedded camera and accelerometer instruments to collect descriptive data in regions of poor road condition. In order to support such a network, an active user base must be established and maintained. User participation is at the heart of creating diverse data pools and addressing quality road condition information. The component needed to satiate users' drive, and to generate the aforementioned benefits, is described as the incentive mechanism.

- Regardless of the incentive mechanism that is being tested, each simulation contains three crucial entities. First entity is the environment, the second entity is the sensing task, and the third entity is the user. Each entity can be described by behaviors and interactions between each other.
- The above figure shows the entities being placed on a yellow board. In this case the board itself is the environment housing different locational data. The sensing tasks are what holds the rewards for users' participation and contain coordinates to describe their location.
- Besides the green tasks are the users. Both the sensing tasks and the users are randomly placed on the board at the start of each simulated experiment.

- OBJECTIVE

The motivation of this project is to derive a brief understanding of monetary incentive mechanisms, and the complexities involved with creating an economically feasible, encompassing method for crowd participation. The technique used to observe the different incentive mechanisms is experimentation through simulation. Testing of various hypotheses was conducted over nine unique incentive mechanisms. Each incentive mechanism was designed with the context of road coverage in mind, but the means of manipulating the field of incentives is distinct between them. By comparing the results of each incentive mechanism, the crowdsensing solution obtains a more resolved version of which incentive mechanism is required to build a crowdsensing platform.

- SURFACE PLOTS

In total there were 9,000,000 subtrials to generate 36, 100x100 datapoint surfaces. In the above figure there are four surfaces representing the four dependent variables: success rate, simulation time, operation cost, and platform cost per sensing task. This incentive mechanism is known as static uniform monetary. Due to the simplicity of the reward assignments, the sensing tasks on average contained higher incentives than the other static and dynamic monetary incentive mechanisms tested. Higher rewards appear to have contributed to a boost in success rate, but the platform's cost when assigning sensing tasks was relatively high due to the lack of price adjustment.

On the other hand, this incentive mechanism performed with the smallest user operation cost on average. This may be for one of two reasons. First, if the platform cost per sensing task is high, then the reward per captured sensing task is high for users, thus there are more users participating through the subtrial; and if there is more participation for later rounds, then there will be less of a need for a singular user to finish a sensing that is further way. Because the simulation cost refers to the sum of all users traveling, then a more distributed load of user travel will lead to less user operation cost. The second reason is that the greedy selection algorithm used by users favors high value sensing tasks. This will be further explored in the Traveling Salesman Problem section.

- TAXONOMY OF INCENTIVE MECHANISMS

The classification scheme of incentive mechanisms can be broken down into monetary and non-monetary based incentive mechanisms. Monetary incentive mechanisms rely on the direct backing of fiat money or indirect backing of fiat money through alternative currencies. Hence, most theorized examples are framed as classical microeconomic problems. Non-monetary incentive mechanisms rely on the continual participation of users due to intrinsic motivations. These mechanisms usually are in the form of a game. One conclusion of the survey is that monetary incentive mechanisms are more economically feasible than non-monetary incentive mechanisms. Therefore, a monetary incentive mechanism is more fitting for a crowdsensing solution and will be the consideration of this report.

- **Traveling Salesman Problem**

In the above figure, the static uniform monetary incentive mechanism is compared to two unique dynamic monetary incentive mechanisms. Dynamic predict and dynamic relative are incentive mechanisms that utilize computational prediction to look one to three moves ahead in order to select the local optimal sensing task. While these solutions do not scale well, and should not be considered when attempting to create a crowdsensing platform, they offer insight on the complexity of the multiple user optimum predicted budget and area coverage problem.

The multiple traveling salesmen problem is a classic version of this dilemma. Theoretically speaking, the optimal solution for an incentive mechanism would be one that can reduce the cost, increase the success rate, and minimize the simulation time. The only way that this can be done is if the incentive mechanism solves the multiple traveling salesmen np-hard problem. Given an environment with 50 sensing tasks, and the exponential increase in time complexity, such a solution would take centuries to develop.

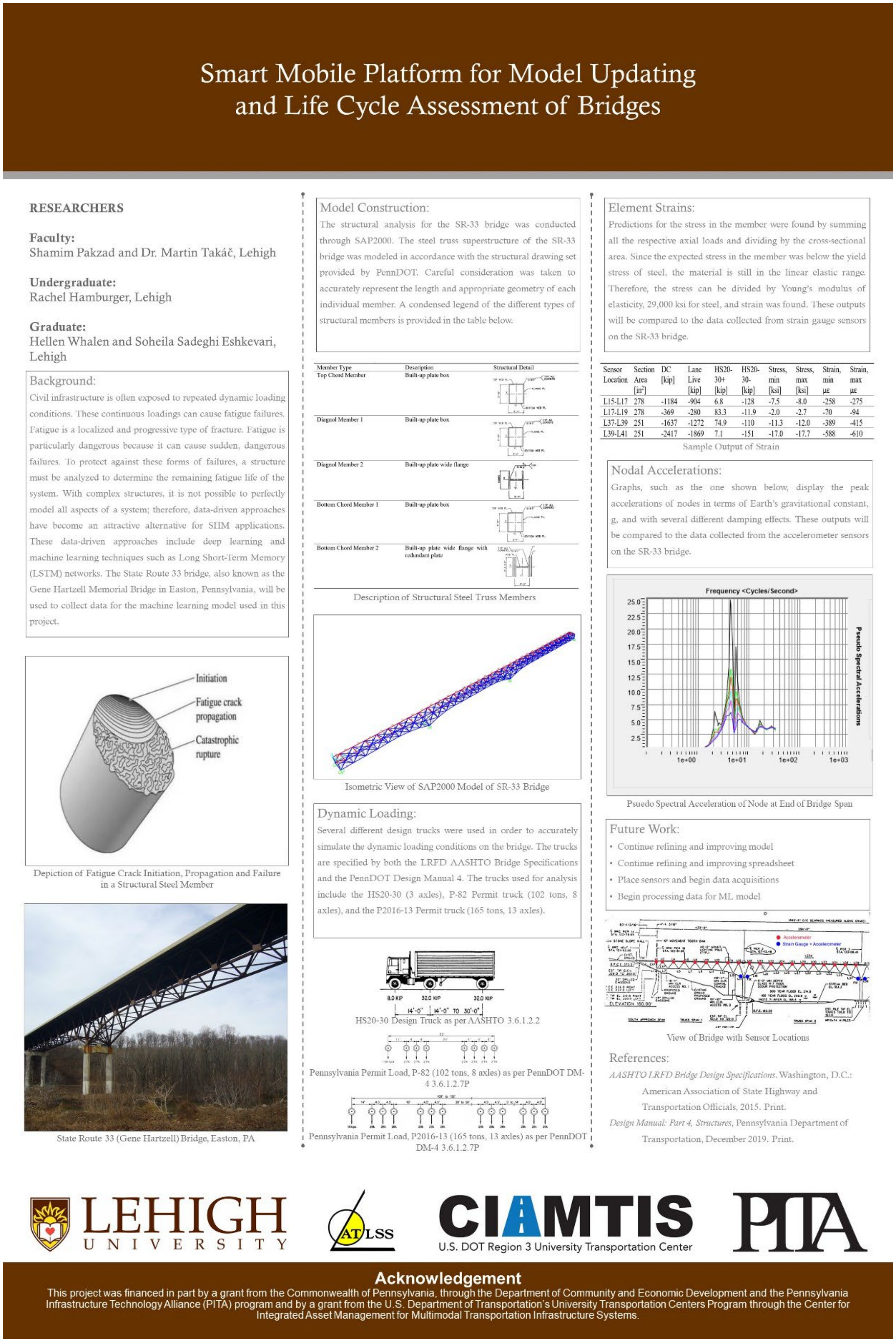
Attempts to find smaller optimal sensing task groups also prove useless as shown by the performance panels above. Neither the short-term prediction algorithm nor the relative distancing algorithm could outperform the simplest of static monetary incentive mechanisms.

The reason for this is because not only is the graph representation for the shortest path difficult to generate over three combinations of sensing tasks, but also the graph is subject to change externally from outsider users.

Acknowledgement

This project was financed in part by a grant from the Commonwealth of Pennsylvania, through the Department of Community and Economic Development and the Pennsylvania Infrastructure Technology Alliance (PITA) program and by a grant from the U.S. Department of Transportation's University Transportation Centers Program through the Center for Integrated Asset Management for Multimodal Transportation Infrastructure Systems.

Figure 5. Project poster for CIAMTIS project entitled *Road Pavement Condition Monitoring by Embedded Crowdsensing.*



Smart Mobile Platform for Model Updating and Life Cycle Assessment of Bridges

RESEARCHERS

Faculty:
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Undergraduate:
Rachel Hamburger, Lehigh

Graduate:
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Background:

Civil infrastructure is often exposed to repeated dynamic loading conditions. These continuous loadings can cause fatigue failures. Fatigue is a localized and progressive type of fracture. Fatigue is particularly dangerous because it can cause sudden, dangerous failures. To protect against these forms of failures, a structure must be analyzed to determine the remaining fatigue life of the system. With complex structures, it is not possible to perfectly model all aspects of a system; therefore, data-driven approaches have become an attractive alternative for SHM applications. These data-driven approaches include deep learning and machine learning techniques such as Long Short-Term Memory (LSTM) networks. The State Route 33 bridge, also known as the Gene Hartzell Memorial Bridge in Easton, Pennsylvania, will be used to collect data for the machine learning model used in this project.

Depiction of Fatigue Crack Initiation, Propagation and Failure in a Structural Steel Member

State Route 33 (Gene Hartzell) Bridge, Easton, PA

Model Construction:

The structural analysis for the SR-33 bridge was conducted through SAP2000. The steel truss superstructure of the SR-33 bridge was modeled in accordance with the structural drawing set provided by PennDOT. Careful consideration was taken to accurately represent the length and appropriate geometry of each individual member. A condensed legend of the different types of structural members is provided in the table below.

Member Type	Description	Structural Detail
Top Chord Member	Built-up plate box	
Diagnol Member 1	Built-up plate box	
Diagnol Member 2	Built-up plate wide flange	
Bottom Chord Member 1	Built-up plate box	
Bottom Chord Member 2	Built-up plate wide flange with redundant plate	

Description of Structural Steel Truss Members

Isometric View of SAP2000 Model of SR-33 Bridge

Dynamic Loading:

Several different design trucks were used in order to accurately simulate the dynamic loading conditions on the bridge. The trucks are specified by both the LRFD AASHTO Bridge Specifications and the PennDOT Design Manual 4. The trucks used for analysis include the HS20-30 (3 axles), P-82 Permit truck (102 tons, 8 axles), and the P2016-13 Permit truck (165 tons, 13 axles).

HS20-30 Design Truck as per AASHTO 3.6.1.2.2

Pennsylvania Permit Load, P-82 (102 tons, 8 axles) as per PennDOT DM-4 3.6.1.2.7P

Pennsylvania Permit Load, P2016-13 (165 tons, 13 axles) as per PennDOT DM-4 3.6.1.2.7P

Element Strains:

Predictions for the stress in the member were found by summing all the respective axial loads and dividing by the cross-sectional area. Since the expected stress in the member was below the yield stress of steel, the material is still in the linear elastic range. Therefore, the stress can be divided by Young's modulus of elasticity, 29,000 ksi for steel, and strain was found. These outputs will be compared to the data collected from strain gauge sensors on the SR-33 bridge.

Sensor Location	Section Area [in^2]	DC [kip]	Lane Live [kip]	HS20-30+ [kip]	HS20-30- [kip]	Stress, min [ksi]	Stress, max [ksi]	Strain, min με	Strain, max με
L15-L17	278	-1184	-904	6.8	-128	-7.5	-8.0	-258	-275
L17-L19	278	-369	-280	83.3	-11.9	-2.0	-2.7	-70	-94
L37-L39	251	-1637	-1272	74.9	-110	-11.3	-12.0	-389	-415
L39-L41	251	-2417	-1869	7.1	-151	-17.0	-17.7	-588	-610

Sample Output of Strain

Nodal Accelerations:

Graphs, such as the one shown below, display the peak accelerations of nodes in terms of Earth's gravitational constant, g, and with several different damping effects. These outputs will be compared to the data collected from the accelerometer sensors on the SR-33 bridge.

Psuedo Spectral Acceleration of Node at End of Bridge Span

Future Work:

- Continue refining and improving model
- Continue refining and improving spreadsheet
- Place sensors and begin data acquisitions
- Begin processing data for ML model

View of Bridge with Sensor Locations

References:

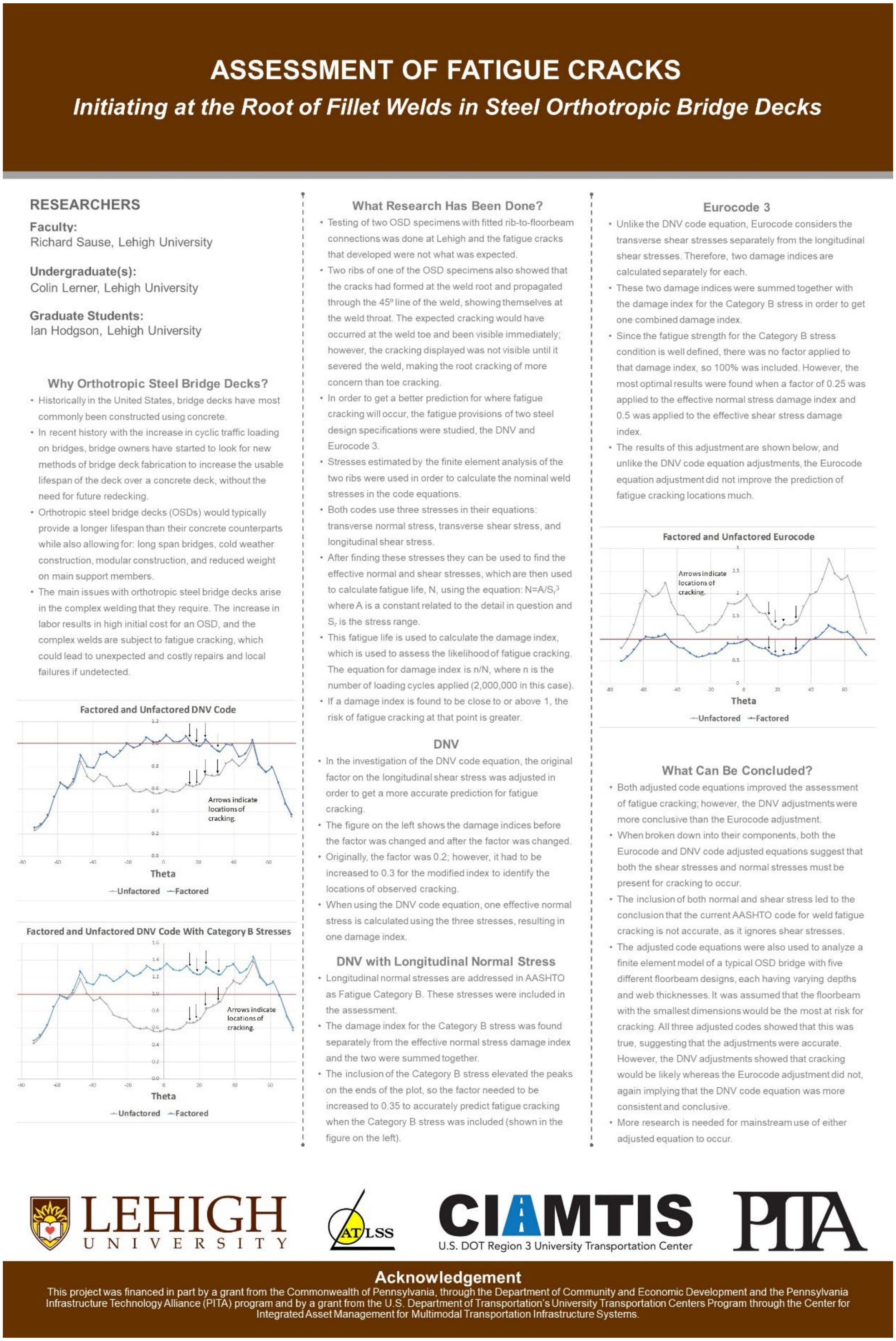
AASHTO LRFD Bridge Design Specifications. Washington, D.C.: American Association of State Highway and Transportation Officials, 2015. Print.

Design Manual: Part 4, Structures, Pennsylvania Department of Transportation, December 2019. Print.

Acknowledgement

This project was financed in part by a grant from the Commonwealth of Pennsylvania, through the Department of Community and Economic Development and the Pennsylvania Infrastructure Technology Alliance (PITA) program and by a grant from the U.S. Department of Transportation's University Transportation Centers Program through the Center for Integrated Asset Management for Multimodal Transportation Infrastructure Systems.

Figure 6. Project poster for CIAMTIS project entitled *Smart Mobile Platform for Model Updating and Life Cycle Assessment of Bridges*.



ASSESSMENT OF FATIGUE CRACKS

Initiating at the Root of Fillet Welds in Steel Orthotropic Bridge Decks

RESEARCHERS

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Why Orthotropic Steel Bridge Decks?

- Historically in the United States, bridge decks have most commonly been constructed using concrete.
- In recent history with the increase in cyclic traffic loading on bridges, bridge owners have started to look for new methods of bridge deck fabrication to increase the usable lifespan of the deck over a concrete deck, without the need for future redecking.
- Orthotropic steel bridge decks (OSDs) would typically provide a longer lifespan than their concrete counterparts while also allowing for: long span bridges, cold weather construction, modular construction, and reduced weight on main support members.
- The main issues with orthotropic steel bridge decks arise in the complex welding that they require. The increase in labor results in high initial cost for an OSD, and the complex welds are subject to fatigue cracking, which could lead to unexpected and costly repairs and local failures if undetected.

Factored and Unfactored DNV Code

Factored and Unfactored DNV Code With Category B Stresses

What Research Has Been Done?

- Testing of two OSD specimens with fitted rib-to-floorbeam connections was done at Lehigh and the fatigue cracks that developed were not what was expected.
- Two ribs of one of the OSD specimens also showed that the cracks had formed at the weld root and propagated through the 45° line of the weld, showing themselves at the weld throat. The expected cracking would have occurred at the weld toe and been visible immediately; however, the cracking displayed was not visible until it severed the weld, making the root cracking of more concern than toe cracking.
- In order to get a better prediction for where fatigue cracking will occur, the fatigue provisions of two steel design specifications were studied, the DNV and Eurocode 3.
- Stresses estimated by the finite element analysis of the two ribs were used in order to calculate the nominal weld stresses in the code equations.
- Both codes use three stresses in their equations: transverse normal stress, transverse shear stress, and longitudinal shear stress.
- After finding these stresses they can be used to find the effective normal and shear stresses, which are then used to calculate fatigue life, N, using the equation: $N=A/S_r^3$ where A is a constant related to the detail in question and S_r is the stress range.
- This fatigue life is used to calculate the damage index, which is used to assess the likelihood of fatigue cracking. The equation for damage index is n/N, where n is the number of loading cycles applied (2,000,000 in this case).
- If a damage index is found to be close to or above 1, the risk of fatigue cracking at that point is greater.

DNV

- In the investigation of the DNV code equation, the original factor on the longitudinal shear stress was adjusted in order to get a more accurate prediction for fatigue cracking.
- The figure on the left shows the damage indices before the factor was changed and after the factor was changed.
- Originally, the factor was 0.2; however, it had to be increased to 0.3 for the modified index to identify the locations of observed cracking.
- When using the DNV code equation, one effective normal stress is calculated using the three stresses, resulting in one damage index.

DNV with Longitudinal Normal Stress

- Longitudinal normal stresses are addressed in AASHTO as Fatigue Category B. These stresses were included in the assessment.
- The damage index for the Category B stress was found separately from the effective normal stress damage index and the two were summed together.
- The inclusion of the Category B stress elevated the peaks on the ends of the plot, so the factor needed to be increased to 0.35 to accurately predict fatigue cracking when the Category B stress was included (shown in the figure on the left).

Eurocode 3

- Unlike the DNV code equation, Eurocode considers the transverse shear stresses separately from the longitudinal shear stresses. Therefore, two damage indices are calculated separately for each.
- These two damage indices were summed together with the damage index for the Category B stress in order to get one combined damage index.
- Since the fatigue strength for the Category B stress condition is well defined, there was no factor applied to that damage index, so 100% was included. However, the most optimal results were found when a factor of 0.25 was applied to the effective normal stress damage index and 0.5 was applied to the effective shear stress damage index.
- The results of this adjustment are shown below, and unlike the DNV code equation adjustments, the Eurocode equation adjustment did not improve the prediction of fatigue cracking locations much.

Factored and Unfactored Eurocode

What Can Be Concluded?

- Both adjusted code equations improved the assessment of fatigue cracking; however, the DNV adjustments were more conclusive than the Eurocode adjustment.
- When broken down into their components, both the Eurocode and DNV code adjusted equations suggest that both the shear stresses and normal stresses must be present for cracking to occur.
- The inclusion of both normal and shear stress led to the conclusion that the current AASHTO code for weld fatigue cracking is not accurate, as it ignores shear stresses.
- The adjusted code equations were also used to analyze a finite element model of a typical OSD bridge with five different floorbeam designs, each having varying depths and web thicknesses. It was assumed that the floorbeam with the smallest dimensions would be the most at risk for cracking. All three adjusted codes showed that this was true, suggesting that the adjustments were accurate. However, the DNV adjustments showed that cracking would be likely whereas the Eurocode adjustment did not, again implying that the DNV code equation was more consistent and conclusive.
- More research is needed for mainstream use of either adjusted equation to occur.

Acknowledgement

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Figure 7. Project poster for CIAMTIS project entitled *Assessment of Fatigue Cracks Initiating at the Root of Fillet Welds in Steel Orthotropic Bridge Decks*

The REU Program

Beyond the research project, the students engaged in various professional development activities throughout the duration of the 10-week program, as outlined below:

- Orientation and Training sessions:
  - Program orientation focused around the ensuing REU program in addition to the CIAMTIS UTC and ATLSS Engineering Research Center
  - NHERI Lehigh Experimental Facility Overview and Training – Lehigh University operates the National Science Foundation funded Natural Hazards Engineering Research Infrastructure (NHERI) Real-Time Multi-Directional Experimental Facility within the ATLSS Engineering Research Center
  - Technical report writing presentation
- Professional development sessions:
  - *Library Resources and Research* by Philip Hewitt, Engineering and Electronic Collections Librarian, Lehigh University
  - *Getting Started on Your Career Journey* by Katharine Marianacci, Associate Director, Career Services, Lehigh University
  - *Resume/Cover Letter Lab* by Katharine Marianacci, Associate Director, Career Services, Lehigh University
  - *How to Conduct an Effective Internship/Job Search* by Katharine Marianacci, Associate Director, Career Services, Lehigh University
  - *Building Your Professional Network* by Katharine Marianacci, Associate Director, Career Services, Lehigh University
  - *Interview Skills Workshop* by Katharine Marianacci, Associate Director, Career Services, Lehigh University
- Research activities:
  - Students submitted weekly reflections and made project updated presentations to other REU program students as part of weekly program group meetings.
- Final Presentations:
  - Students made 15-minute final presentations with accompanying question and answer session.

CHAPTER 4

Recommendations

FUTURE REU PROGRAM

Participating REU students were provided with a well-rounded professional development experience that focused on conducting research as part of active CIAMTIS research projects at Lehigh University under the direction of project PIs and mentors. Six students also participated in training and orientation sessions, professional development sessions, and research group activities focused on enhancing the students' overall professional skills and exposure.

Lehigh's CIAMTIS administration plans on continuing the REU program in the Summer of 2021.