New Tests & Tools for Highly-Sustainable Asphalt

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ACAF CONVENTION 2021

JUNE 11, 2021

Goal 1 - Motivate to Innovate

innovate

[ˈinəˌvāt]

VERB

make changes in something established, especially by introducing new methods, ideas, or products.

"the company's failure to diversify and innovate competitively"

synonyms: originate · create · design · devise · contrive · formulate · develop · conceive · think up · come up with · hit on · mastermind · pioneer · discover · find · coin · mint · dream up

- introduce (something new, especially a product).
  "innovating new products, developing existing ones"

Source: Merriam-Webster Dictionary

Goal 2 – Innovate in Sustainability

Outline

1. Performance Tests and Specifications for Sustainable Asphalt Design
2. New Materials/Approaches for Sustainable Pavements
3. New AI-based Tools for Rapid Material Design
4. New AI-based Tools for Smart Pavement Monitoring
5. New Demonstration Projects
6. Partnership Opportunities

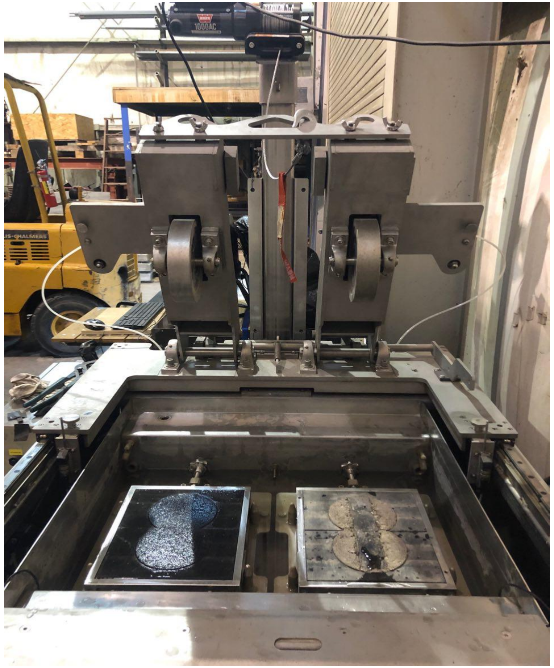
Performance Tests and Specifications

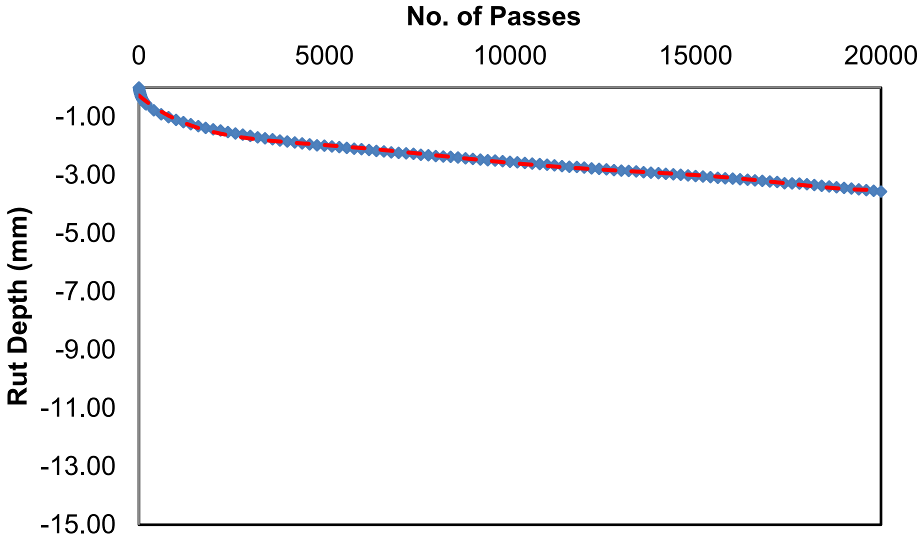
1. **Performance Tests**
   a) Hamburg — Rutting and Stripping
   b) DC(T)
   c) iFIT
   d) IDEAL CT

   Cracking

2. **Balanced Mix Design Specifications**
   a) Illinois Tollway – Various Asphalt Mixture Types
   b) MoDOT – Superpave Asphalt Mixes

Hamburg Wheel-Track Testing (AASHTO T 324)





Determination of Stripping Inflection Point (SIP)

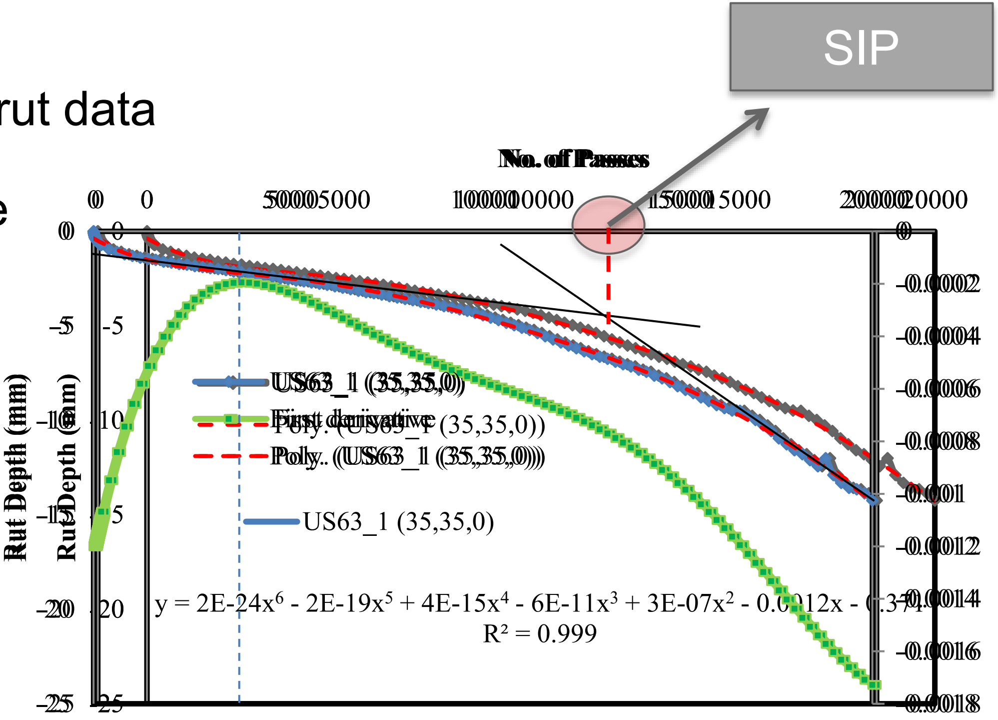
1- Plot rut depth vs. No. of passes

2- Use 6^{th} degree polynomial to fit rut data

3- Calculate and plot first derivative

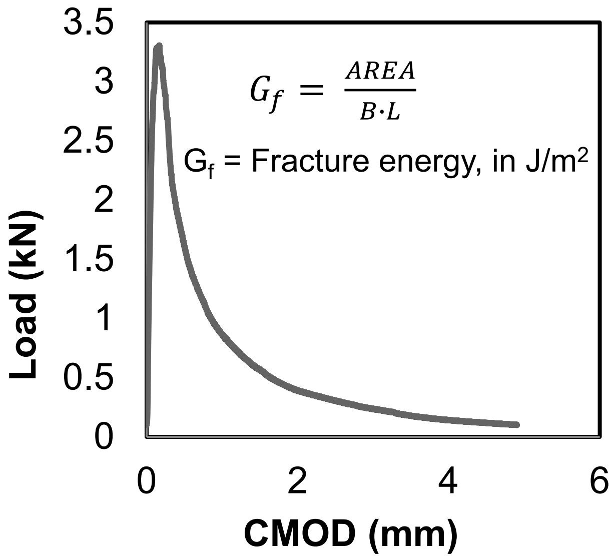
4- Define creep and stripping slopes

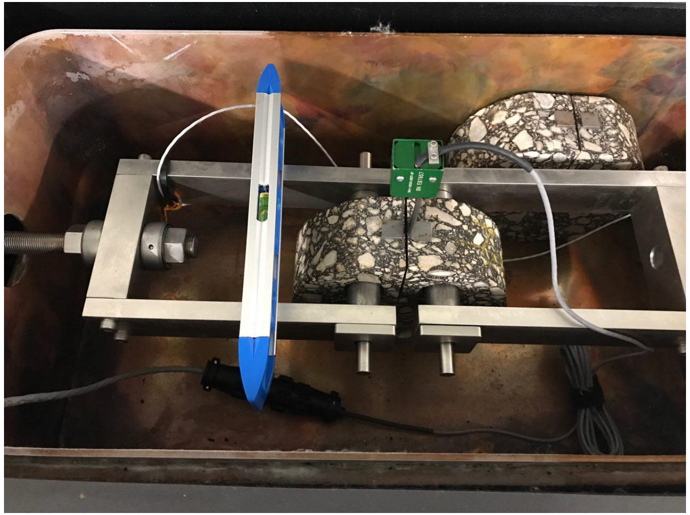
5- Determine the intersection of creep and striping line (SIP)



DC(T) Fracture Test (ASTM D7313)

(Low Temperature/ Block Cracking Control)



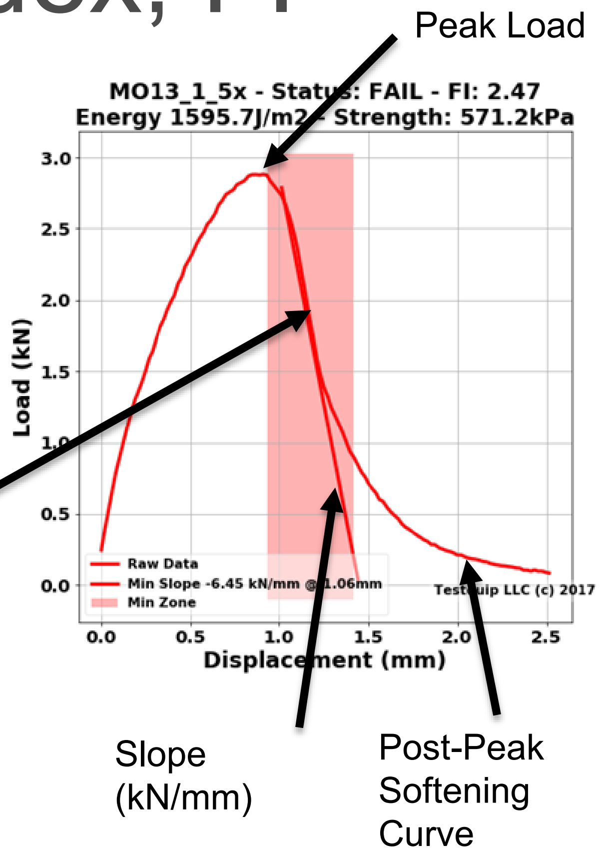


DC(T) Apparatus

I-FIT Flexibility Index, FI

$$FI = \frac{G_f}{|m|}(0.01)$$

- Fracture Energy (G_f) computation is identical to DC(T) procedure
- Slope (m) - tangent of the post-peak 'softening' curve at the <u>point of inflection </u>(absolute value)…some similarity to SIP fitting routine
- The 0.01 multiplier = arbitrary scaling parameter

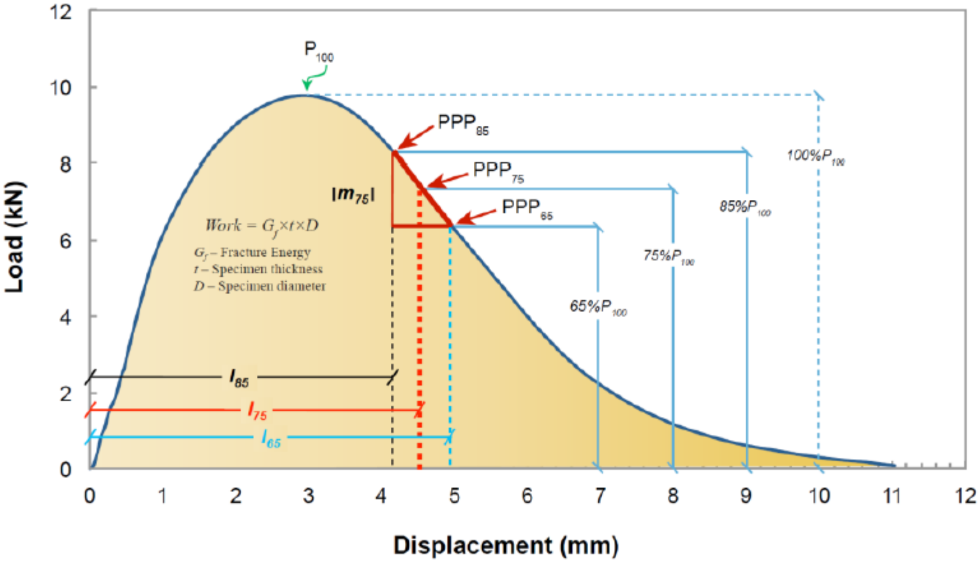


IDEAL CT

Test temperature: 25 ºC

Loading rate: 50mm/min.

Specimen: cylindrical specimen without cutting, gluing, instrumentation, drilling, and notching.



$$CT_{Index} = \frac{t}{62} \times \frac{G_f}{m_{75}} \times \frac{L_{75}}{D}$$

Where:

t = specimen thickness (mm)

G_f = fracture energy (J/m^2);

L_{75}= Displacement corresponding to P75 (mm)

D = Specimen Diameter (mm)

Example of Setting Thresholds for Tests

Setting the border line for DC(T) fracture energy based on *Field Performance Data*

560 J/m^2 at -12 °C

By comparing the Trans/Reflective (O) distress on I294, I90-6.6, and I90-6

Account for Aging

15% increase (Braham et al. 2009)

560*1.15=

644 *J/m^2*

Account for Test Variability and Field Inspection Uncertainty

Add 2*Standard Deviation for ~95% reliability

$644+2*(\frac{70+71}{2}) =$

784 ~ ***<u>775 J/m^2</u>***

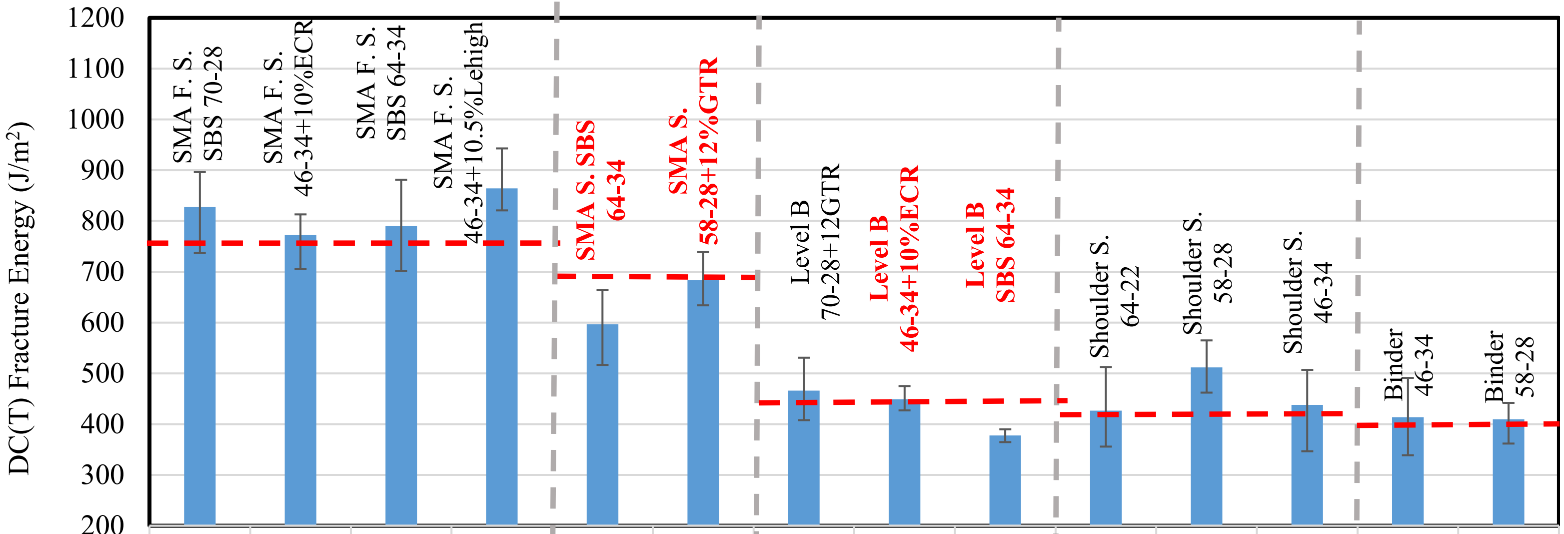
Consensus

<u>775 J/m^2</u>

DC(T) at -12 C

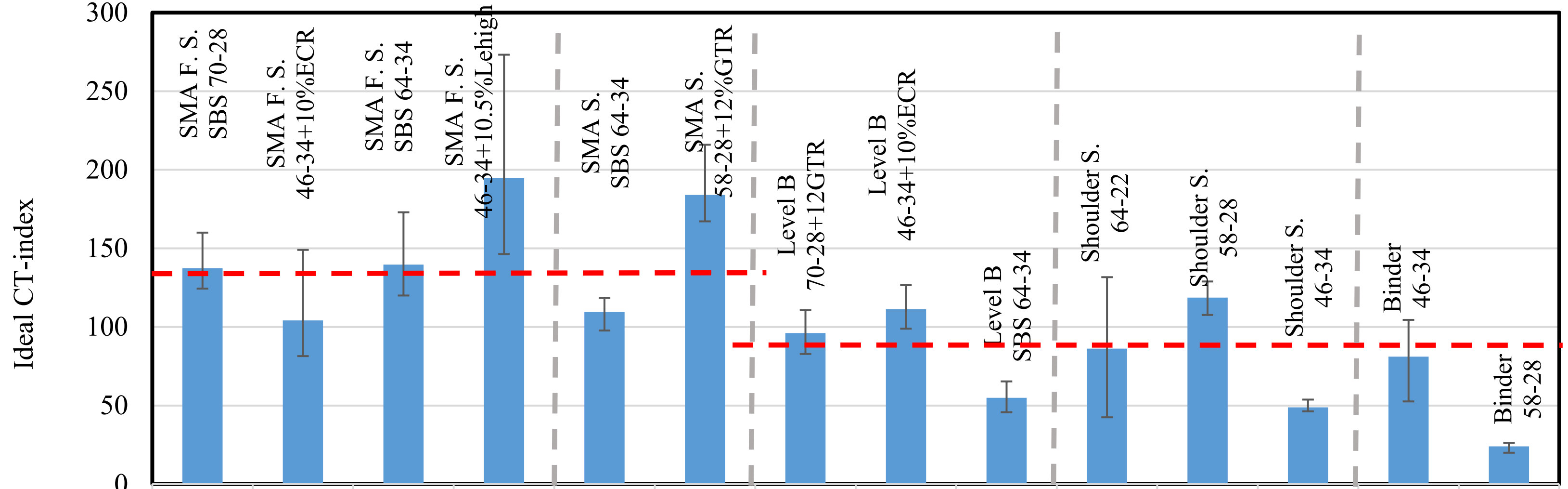
Illinois Tollway Study

Obs.: Compares well with expectations, and criteria; good repeatability, a bit lower than design, due to storage and reheating



	1844	1835	1824	1845	1836	1840	1829	1828	1823	1818	1834	1826	1807	1803
Gf at -12C	827.5	772.3	790.0	864.3	596.5	683.7	466.0	449.0	377.9	426.5	511.7	438.1	413.7	409.7
ABR by RAP	10.8	25.0	20.4	23.9	16.2	15.9	17.8	35.3	24.1	20.4	20.0	27.6	34.4	26.5
ABR by RAS	16.0	16.1	16.7	15.4	16.3	9.8	9.3	9.2	14.2	0.0	0.0	18.1	14.0	16.6
Total ABR	26.8	41.2	37.1	39.3	32.5	25.7	27.0	44.6	38.3	20.4	20.0	45.7	48.4	43.1

IDEAL-CT Testing Results *Illinois Tollway Study*



	1844	1835	1824	1845	1836	1840	1829	1828	1823	1818	1834	1826	1807	1803
CT-index	137.4	104.1	139.6	194.8	109.4	184.0	96.1	111.3	54.9	86.2	118.7	48.8	81.1	24.0
ABR by RAP	10.8	25.0	20.4	23.9	16.2	15.9	17.8	35.3	24.1	20.4	20.0	27.6	34.4	26.5
ABR by RAS	16.0	16.1	16.7	15.4	16.3	9.8	9.3	9.2	14.2	0.0	0.0	18.1	14.0	16.6
Total ABR	26.8	41.2	37.1	39.3	32.5	25.7	27.0	44.6	38.3	20.4	20.0	45.7	48.4	43.1

IL Tollway BMD – Cracking Test Limits

DC(T) thresholds at -12 °C for different mix categories

Mix. Type	Category	Recommended
SMA	Friction Surface	775 J/m^2
	Surface	700 J/m^2
	Binder	650 J/m^2
	Unmodified	500 J/m^2
Dense graded	IL 4.75	450 J/m^2
	Mainline Binder (N_{design}>50)	425 J/m^2
	Mainline Binder (N_{design}=50)	450 J/m^2
	Shoulder Surface (N_{design}≤70)	450 J/m^2
	Shoulder Binders	425 J/m^2

IL Tollway BMD – Hamburg Test Limits

Hamburg rut depth thresholds at 50 °C for different mix categories

Mix. Type	Category	Recommended	
		No. of Passes	Max. Rut Depth
SMA	Friction Surface	20,000	6.0 mm
	Surface	20,000	6.0 mm
	Binder	20,000	6.0 mm
	Unmodified	15,000	12.5 mm[1]
Dense graded	IL 4.75	15,000	12.5 mm
	Mainline Binder (N_{design}>50)	15,000	12.5 mm
	Mainline Binder (N_{design}=50)	10,000	12.5 mm
	Shoulder Surface (N_{design}≤70)	10,000	12.5 mm
	Shoulder Binders	7,500	12.5 mm

IL Tollway BMD – Hamburg SIP Limits

SIP thresholds at 50 ℃ for different mix categories (applied when the slope ratio is ≥ 2.0)

Mix. Type	Category	Recommended
SMA*	Friction Surface	15,000
	Surface	15,000
	Binder	15,000
	Unmodified	10,000
Dense graded	IL 4.75	10,000
	Mainline Binder (N_{design}>50)	10,000
	Mainline Binder (N_{design}=50)	7,500
	Shoulder Surface (N_{design}≤70)	7,500
	Shoulder Binders	5,000

No need to run AASHTO T-283, although optional in case of failing Hamburg result

* If the measured rut depth for SMA mixes at the required number of passes (determined based on Table 7-3) is lower than 4.0 mm, the mix shall be specified as non-stripping without the need to compute the SIP.

MoDOT BMD – Performance Data

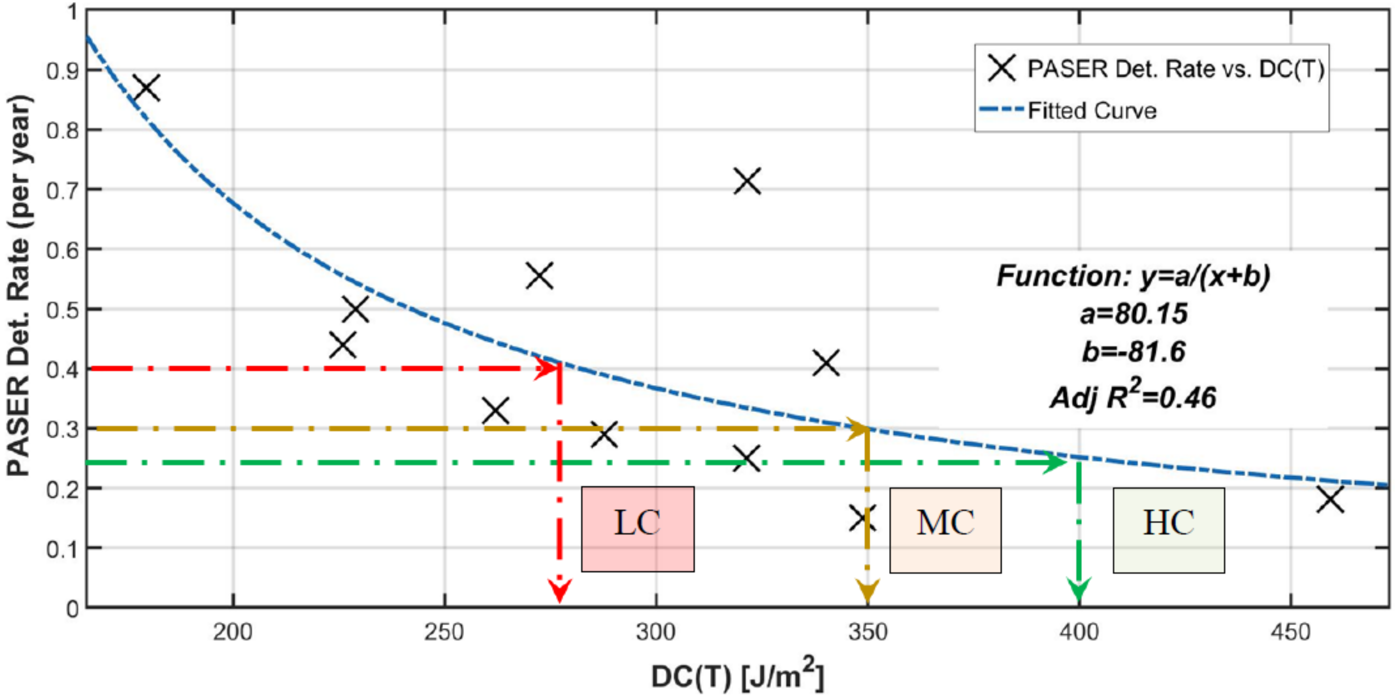


Figure 6-2. Setting baseline DC(T) scores based on PASER Det. Rate for various project criticality levels (HC = high criticality; MC = medium criticality; LC = low criticality)

MoDOT BMD – Performance Data

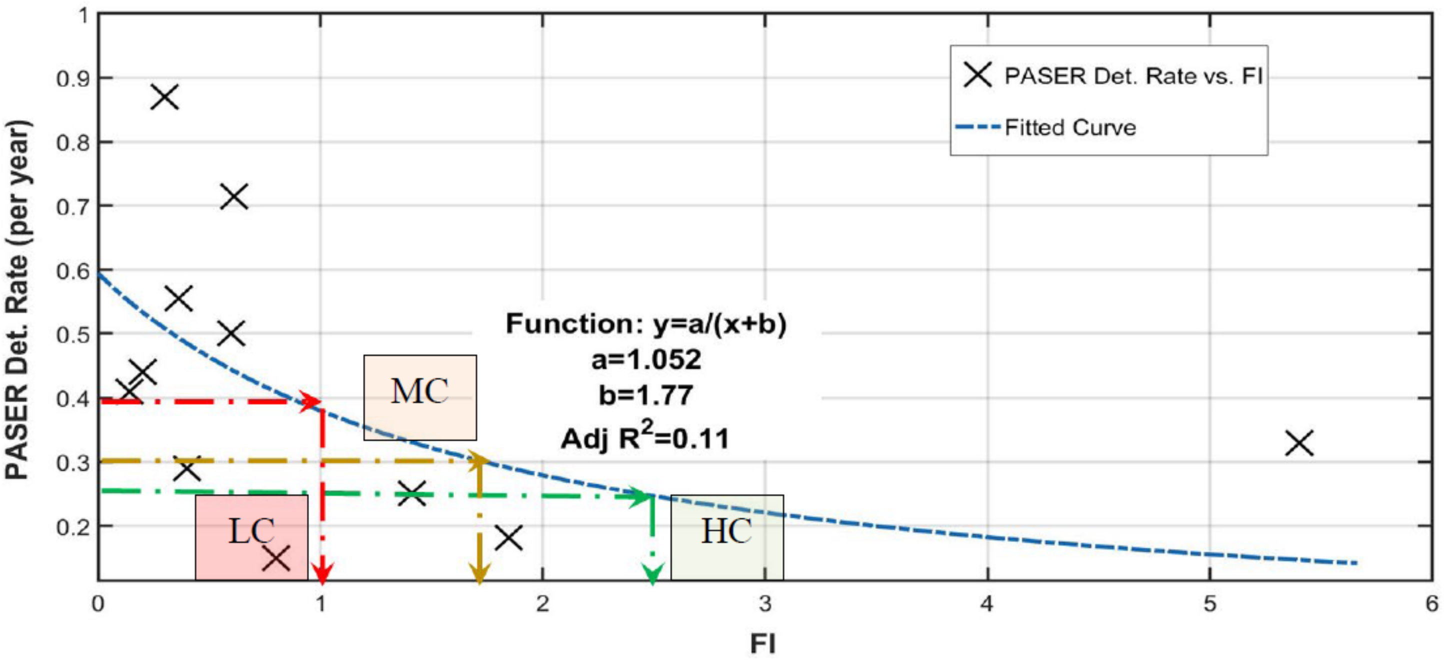


Figure 6-3. Setting baseline FI scores based on PASER Det. Rate for various project criticality levels (HC = high criticality; MC = medium criticality; LC = low criticality)

MoDOT BMD – Recommended Cracking Test Limits, Mainline Pavement

Table 6-2. Recommended cracking test thresholds at -12 ℃ for mainline, non-SMA mixtures

Category	Position in Pavement	Criticality	DC(T) [J/m^2]	FI	IDEAL-CT
a	SL	H	600	14	150
b	SL	M	500	8	100
c	SL	L	400	4	55
d	NSL	H	450	7	100
e	NSL	M	350	5	70
f	NSL	L	300	2	35

MoDOT BMD – Recommended Cracking Test Limits, Shoulders

Table 6-3. Recommended cracking test thresholds at -12 ℃ for shoulder mixtures (also non-SMA)

Category	Position in Pavement	Criticality	DC(T) [J/m^2]	FI	IDEAL-CT
a	SL	H	500	8	100
b	SL	M	400	4	55
c	SL	L	325	3	45
d	NSL	H	350	5	70
e	NSL	M	300	2	35
f	NSL	L	250	1	20

…more details…

DEVELOPMENT OF A PERFORMANCE-RELATED ASPHALT
MIX DESIGN SPECIFICATION FOR THE ILLINOIS TOLLWAY

Final Report
January 19, 2021

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Sponsored by
Illinois State Toll Highway Authority

A report from
The University of Missouri-Columbia
E2509, Lafferre Hall, S Sixth Street,
Columbia, MO 65211.

[https://www.illinoistollway.com/doing-business/construction-engineering/reference-material -](https://www.illinoistollway.com/doing-business/construction-engineering/reference-material)

Support for Balanced Asphalt Mixture Design Specification Development in Missouri

September 2020
Final Report

Project number TR201811
MoDOT Research Report number cmr 20-010

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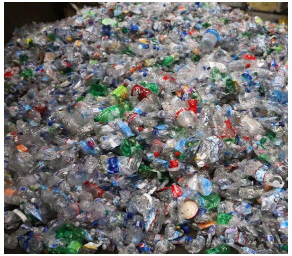
https://spexternal.modot.mo.gov/sites/cm/CORDT/cmr20-010.pdf

Modern, Heterogenous Sustainable Mixes



1993 — 1995 — 2000 — 2020 →

SHRP Project

Polymer Modification

Fibers in Asphalt

RAP and RAS

Rubber Incorporation

Plastic in Asphalt

New Materials/Approaches for Sustainable Pavements

1. Dry-Process Ground Tire Rubber Mixes
2. Dry-Process Waste Plastic Asphalt
3. Combinations of New (above) + Traditional Recyclates and Modifiers (RAP, RAS, Rejuvenators)

Rubber and Plastic Recycling

Rubber and plastic are incredibly tough and durable materials…so durable in fact that they pose considerable end-of-life problems

Can these materials be re-used in America's infrastructure to eliminate single use and promote a more circular economy???

Finalizing the implementation of rubber-modified asphalt, or **RMA,** creates a blueprint for also addressing the **waste plastic** problem

Why modify asphalt with rubber?

1. Performance
2. Sustainability
3. Economics

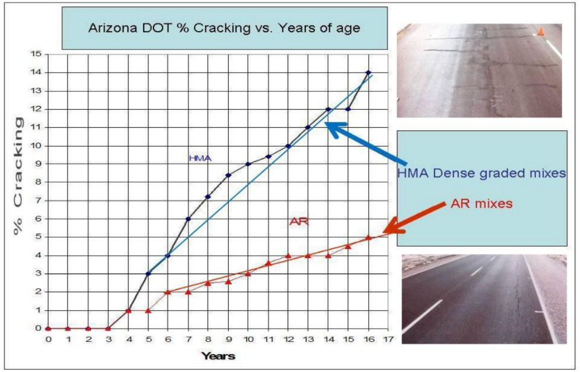
Why modify asphalt with rubber?

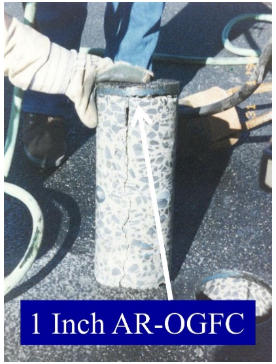
1 **Performance**

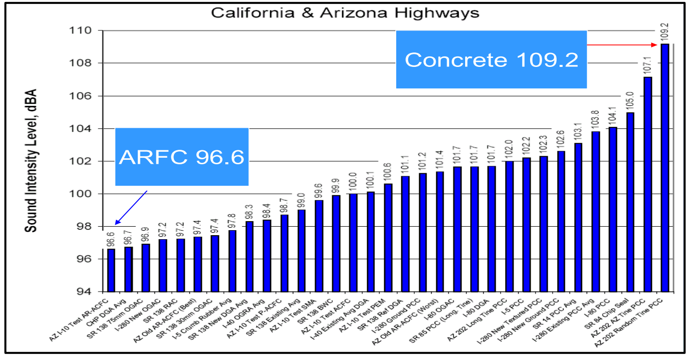
2 Sustainability

3 Economics

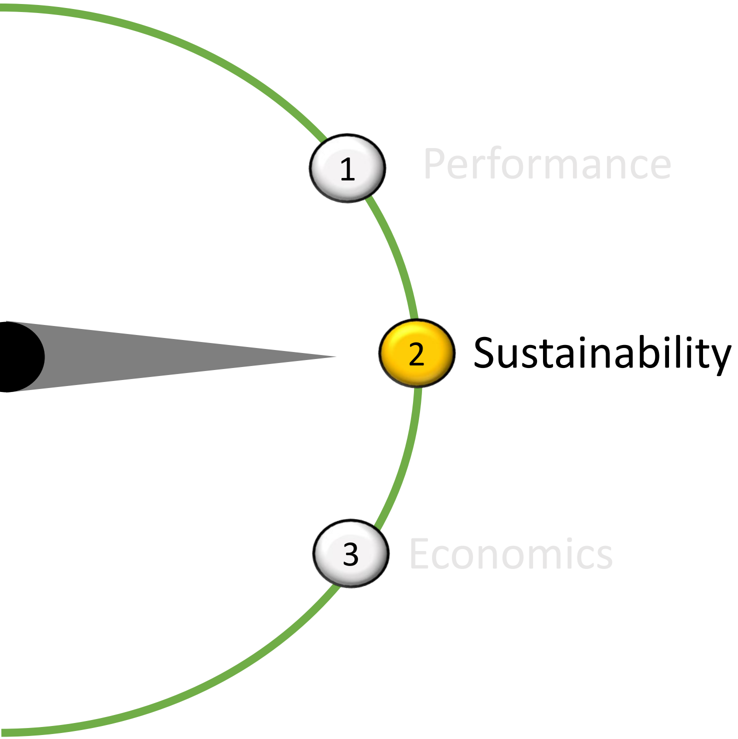
RMA is able to provide performance and functional benefits including **longer service life**, **lower noise**, and **better ride** quality, and **increased skid resistance**



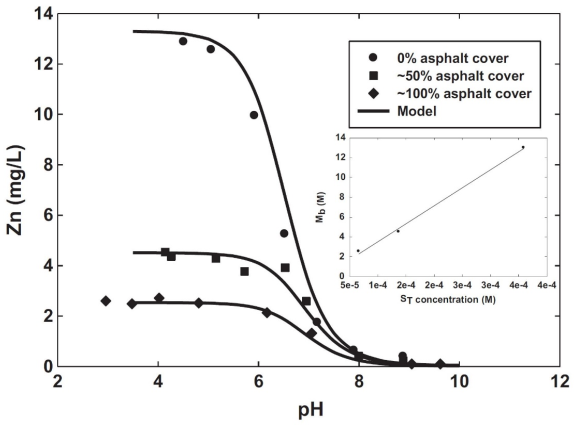




Why modify asphalt with rubber?

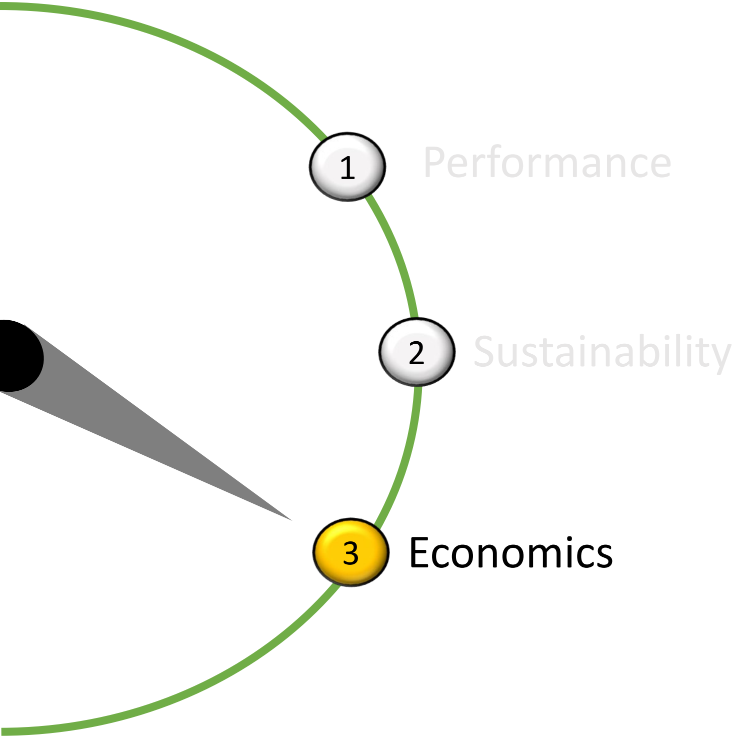


- LCA studies with proper assumptions show **reductions in environmental impact when using RMA**, ~30-40% reduction (more work needed)
- Entombment of rubber particles in asphalt results in **significant decrease in leaching** ~85% reduction (much more work needed)

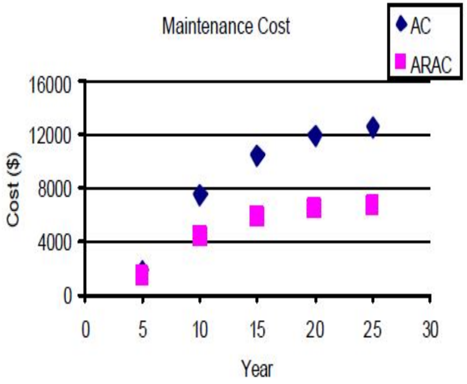


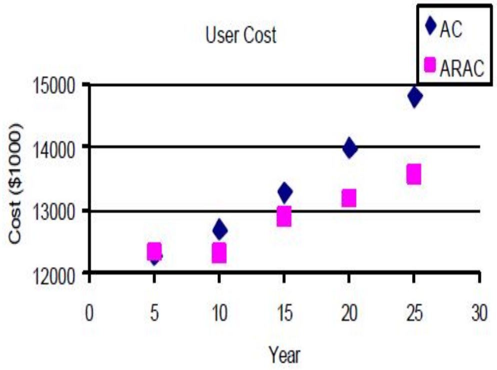
Impact category	*LCA rubberised asphalt road*	*LCA conventional asphalt road*
Climate change (kg CO_2 eq)	10802.81	16337.02
Ozone depletion (kg CFC-11 eq)	4.13E-03	6.66E-03
Human toxicity (kg 1,4-DB eq)	3082.29	4243.56
Photochem oxidant form. (kg NMVOC eq)	67.09	101.65
Terrestrial acidification (kg SO_2 eq)	83.49	128.31
Freshwater eutrophication (kg P eq)	2.92	3.65
Terrestrial ecotoxicity (kg 1,4-DB eq)	3.52	5.60
Freshwater ecotoxicity (kg 1,4-DB eq)	61.45	83.51
Water depletion (m^3)	517.70	742.18
Fossil depletion (kg oil eq)	11506.73	18255.28

Why modify asphalt with rubber?

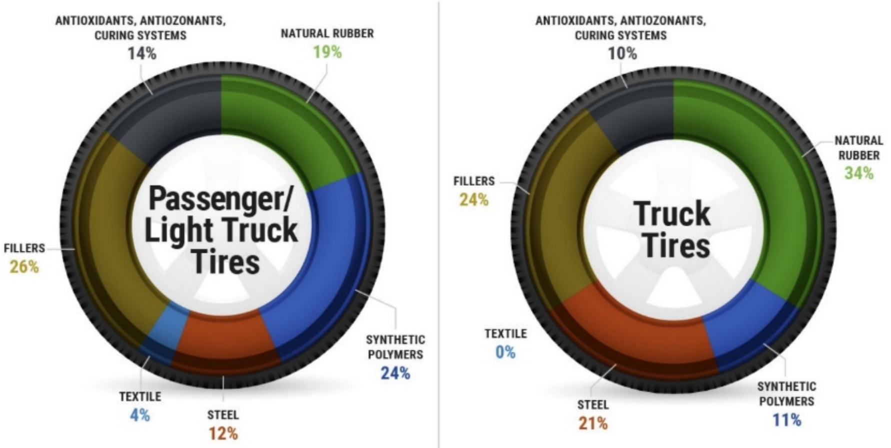


- **Heavy traffic applications**: Modern RMA mixtures are **less expensive than polymer-modified asphalt mixtures** and provide **comparable performance**
- **Light traffic applications:** Life cycle cost studies generally find RMA to be **more cost effective than conventional mixtures**
- **Thin Lift Overlays:** RMA can result in as much as 50% **reduction in lift thickness with same performance**



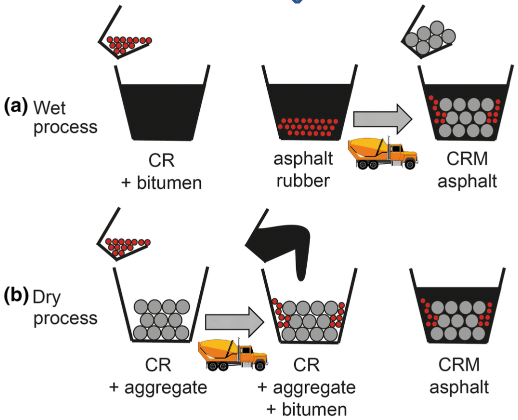


RMA Modification Methods



End of Life Tire Recycling

Ground Tire Rubber (GTR)



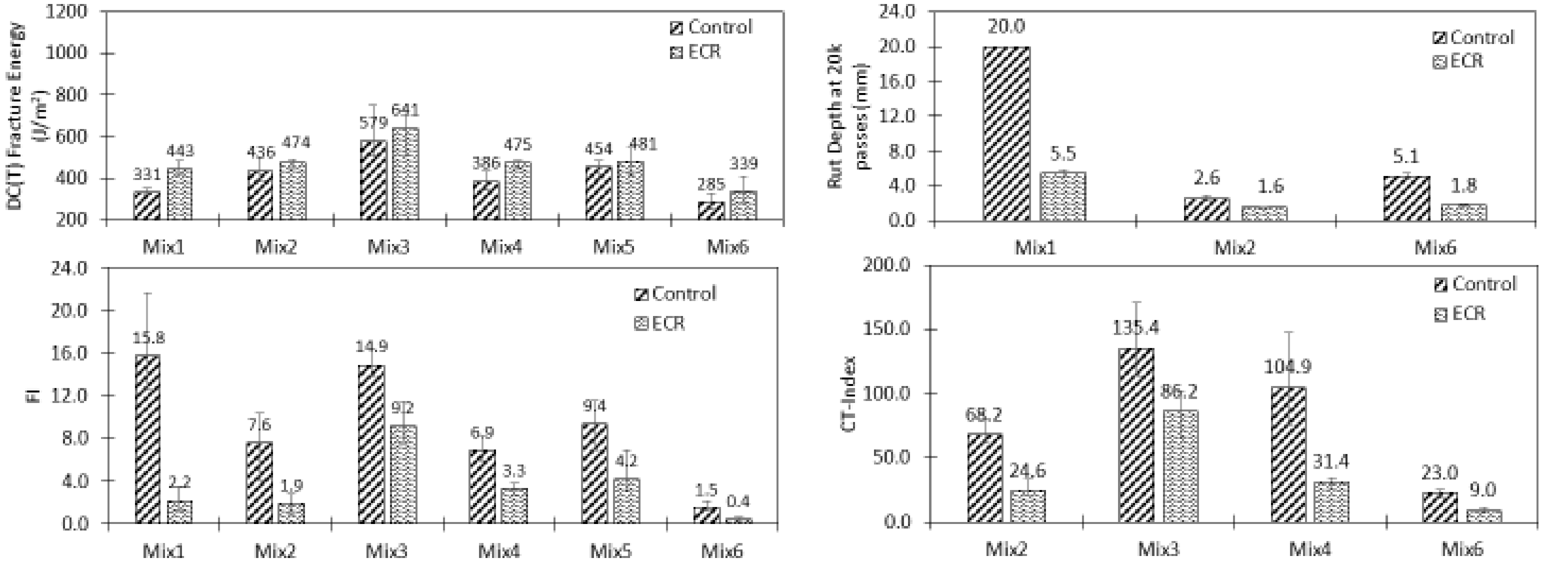
Conventional Paving Equipment/Process

PRECISION PNEUMATIC INJECTION SYSTEM
(Dry-Process GTR or Waste Plastic Pellets)

- MODIFIED FIBER MACHINE
- LOSS-IN-WEIGHT FEEDER
- 2 MIN. ACCURACY: +/- 2%
- 500 MEASUREMENTS/DAY CAPABILITY
- TIED TO BINDER PUMP SPEED
- MAX PLANT OUTPUT: 400 TPH
- ADJUSTABLE FEED RATE FOR ALL MIX DESIGNS

OK RT 3, Oklahoma City, Demo Project

Rubber Modification: Mixture Tests

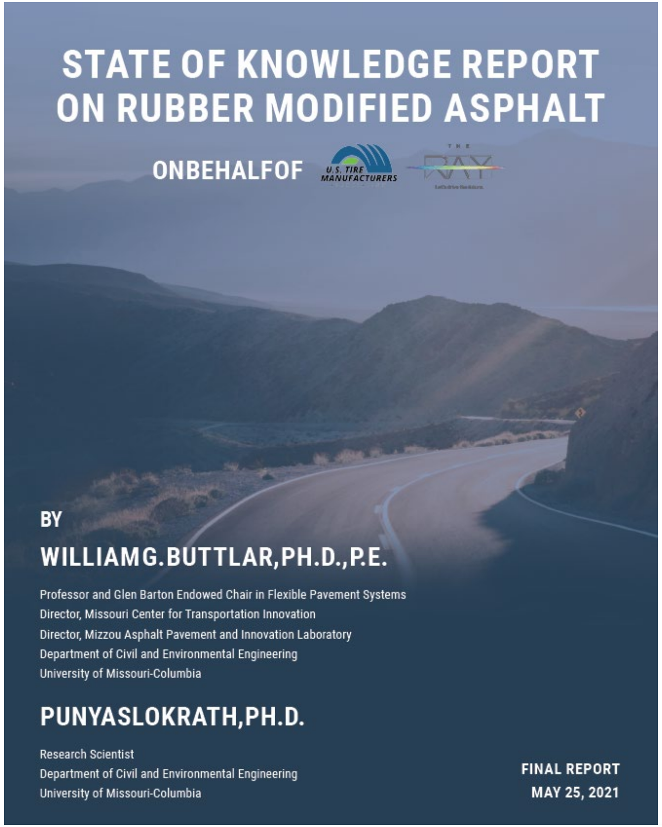


DC(T)	Rut Depth	FI	CT-Index

Correlating Field and Lab Results

- Field performance of dry process GTR is better than conventional pavements and comparable to polymer modified pavements
- More than 5 million mix tons placed in 12 states, four countries
- However certain lab cracking tests results indicate GTR would not perform well. WHY?
  - Research shows that rubber inhibits crack propagation via processes like crack pinning and crack bridging
  - Tests with higher loading rates result in built-up energy in the stiff rubber specimens before the crack begins to propagate
  - The release of this energy in form of crack propagation results in steep post-peak slope
  - Post-peak slope is a dominant factor in the discussed indices, and steep slopes make for lower index values
- Point to note: none of the cracking tests were designed with rubber specimens in the initial test matrix

…more details…



STATE OF KNOWLEDGE REPORT ON RUBBER MODIFIED ASPHALT

ONBEHALFOF U.S. TIRE MANUFACTURERS

BY

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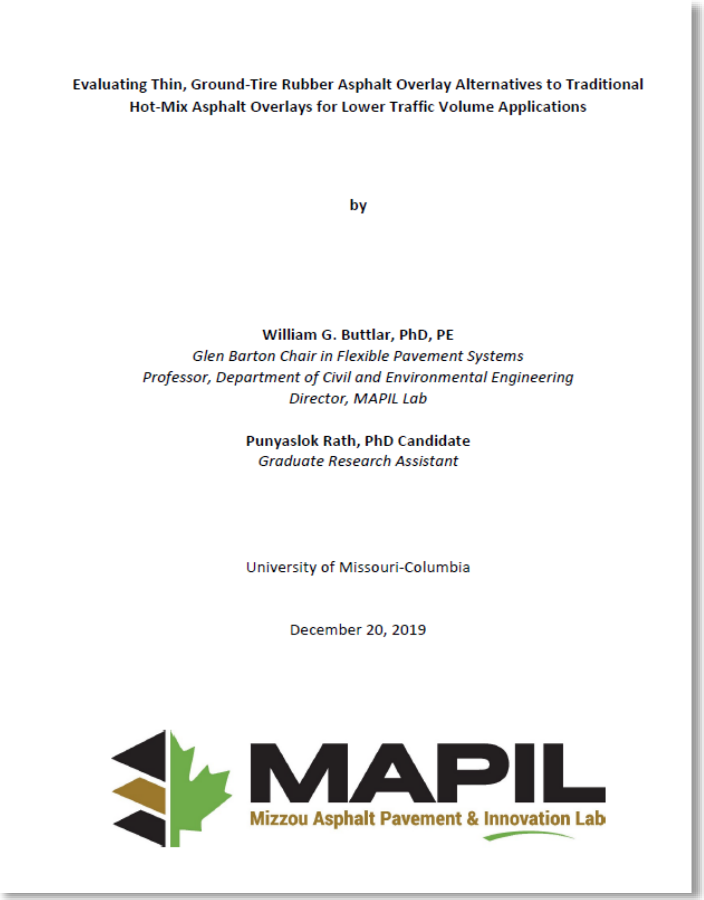
FINAL REPORT
MAY 25, 2021

https://MAPIL.missouri.edu/state-of-knowledge-report-on-rubber-modified-asphalt/



Evaluating Thin, Ground-Tire Rubber Asphalt Overlay Alternatives to Traditional Hot-Mix Asphalt Overlays for Lower Traffic Volume Applications

by

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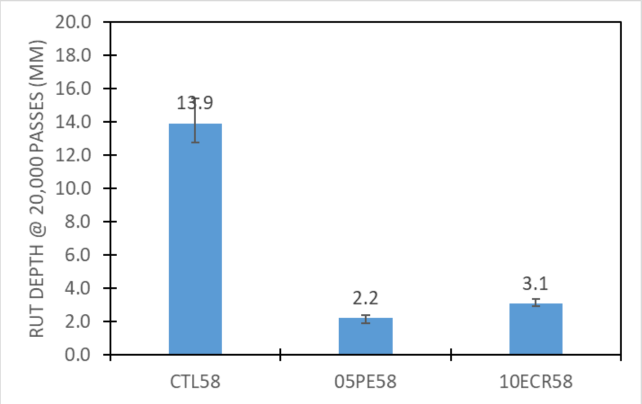
December 20, 2019

MAPIL
Mizzou Asphalt Pavement & Innovation Lab

https://MAPIL.missouri.edu/publications/

Early Work on Dry-Process Waste Plastic in Asphalt

- **Mizzou Collaboration with Dow and MoDOT**
- **Rutting in Hamburg drastically reduced with PE-Rich (LLDPE) pellet or powder**
  - 0.5% - 2.5% by mix weight investigated
  - Pellets do not coat aggregates, partially melt
- **Similar to dry-process GTR:**
  - DC(T) fracture energy slightly increased
  - FI and CT indexes decreased at first
  - Adjustments: regress air voids, use softer binder, adjust rejuvenator / RAP levels
  - Do these materials need their own spec?

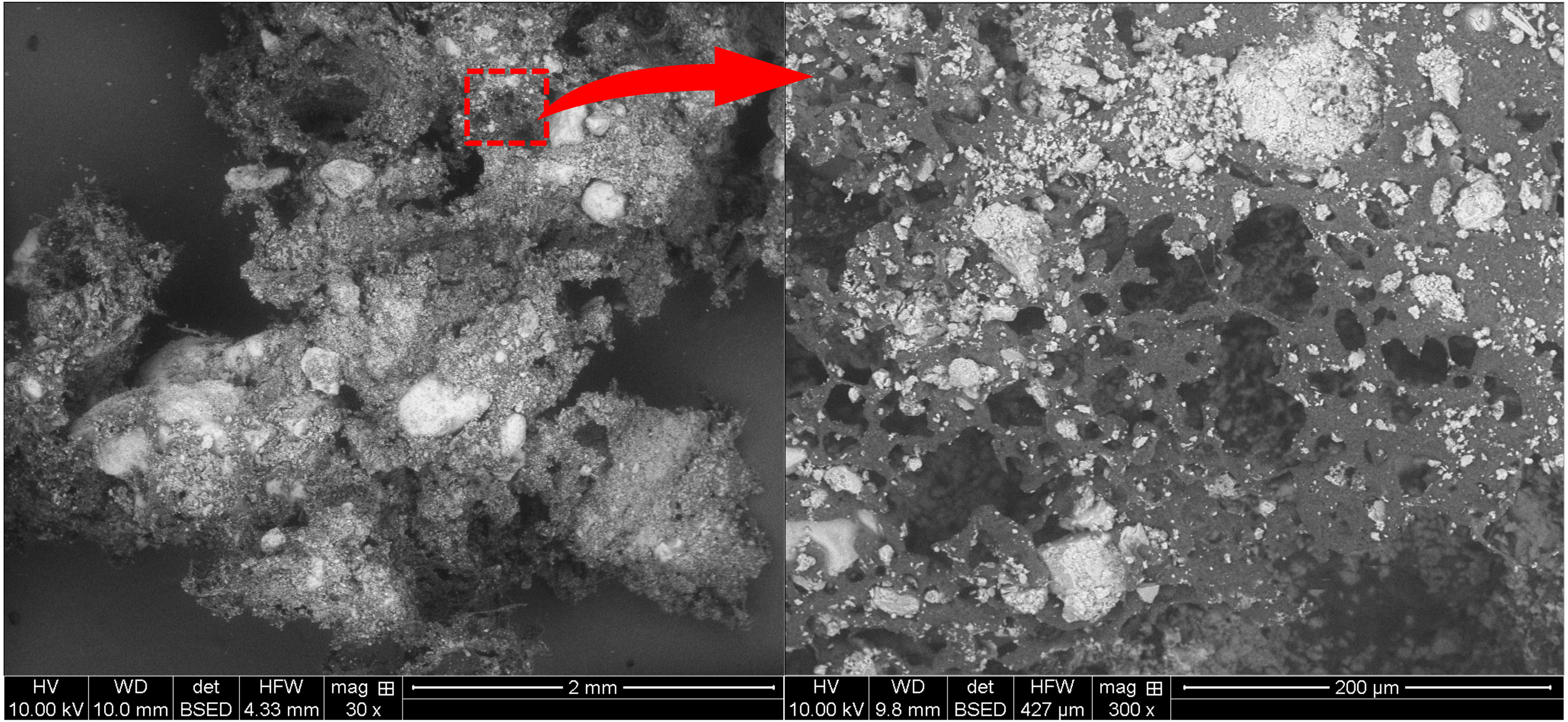


Control Plastic Rubber

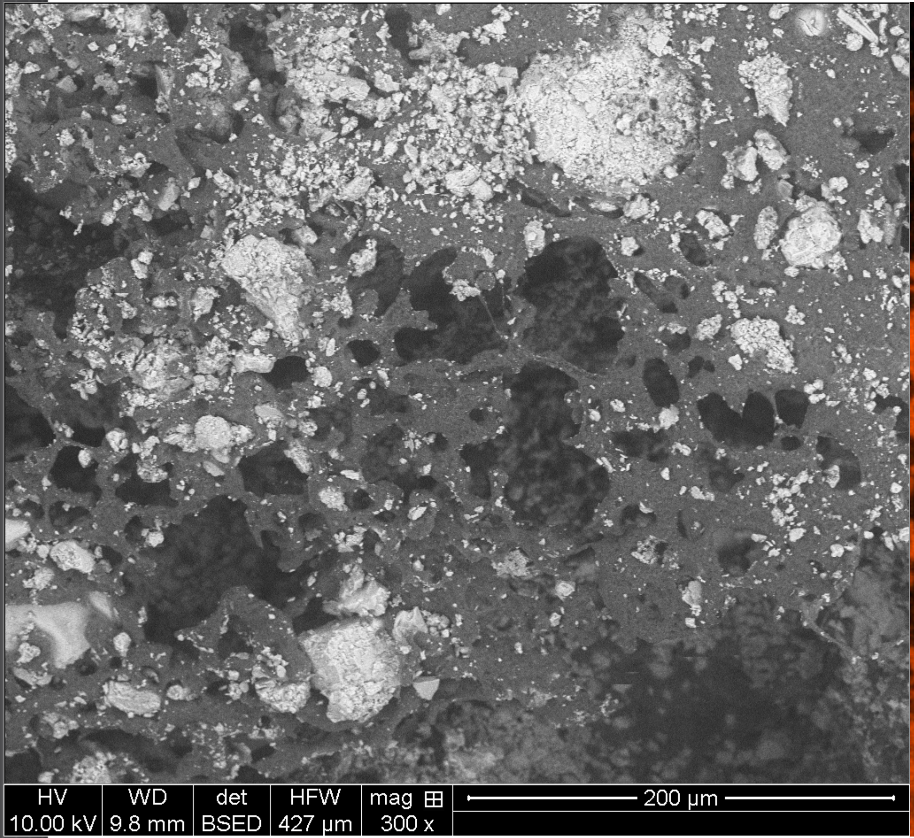
Early Work on Dry-Process Waste Plastic in Asphalt

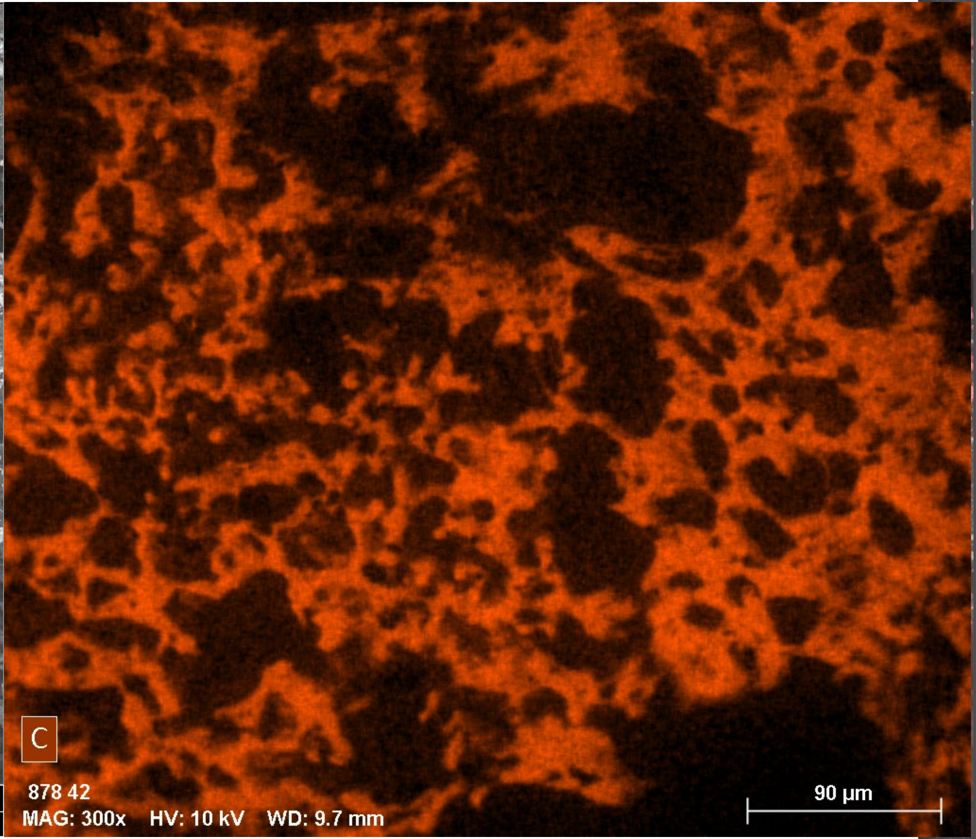
ESEM and stereoscope imaging

Red region is for elemental analysis



EDS mapping

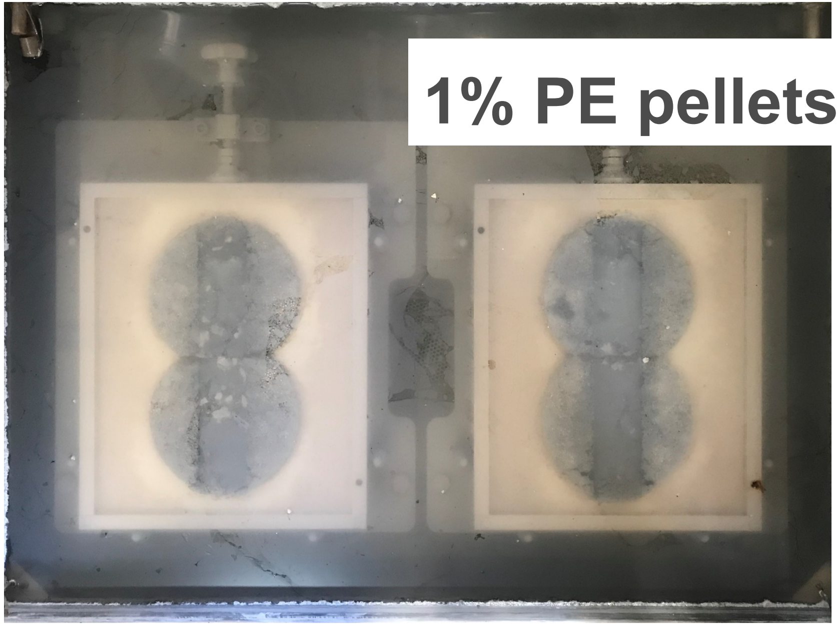

HV
10.00 kV
WD
9.8 mm
det
BSED
HFW
427 µm
mag
300 x
200 µm


C
878 42
MAG: 300x HV: 10 kV WD: 9.7 mm
90 µm

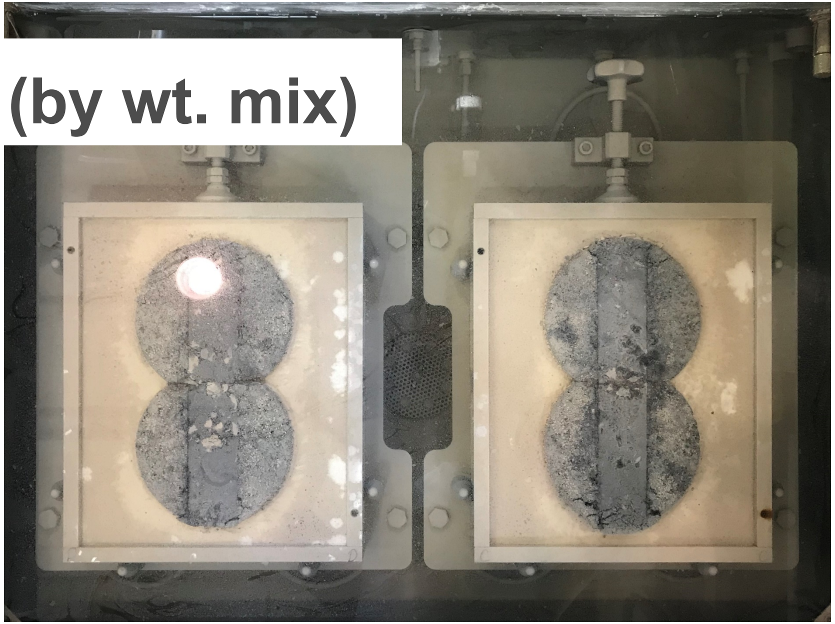
Water Quality Validation

Collaboration with Environmental Engineering Group at Mizzou

1% PE pellets (by wt. mix)



Before surface water collection

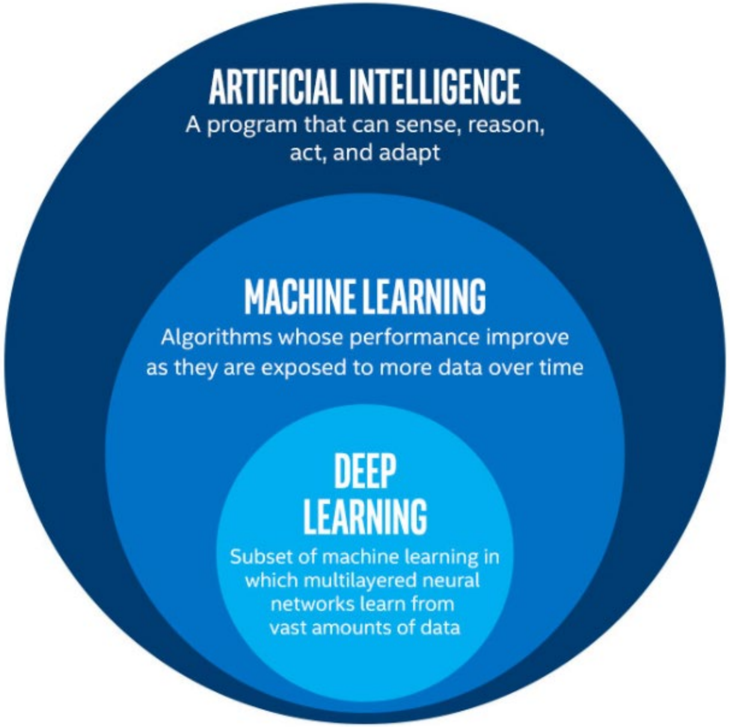


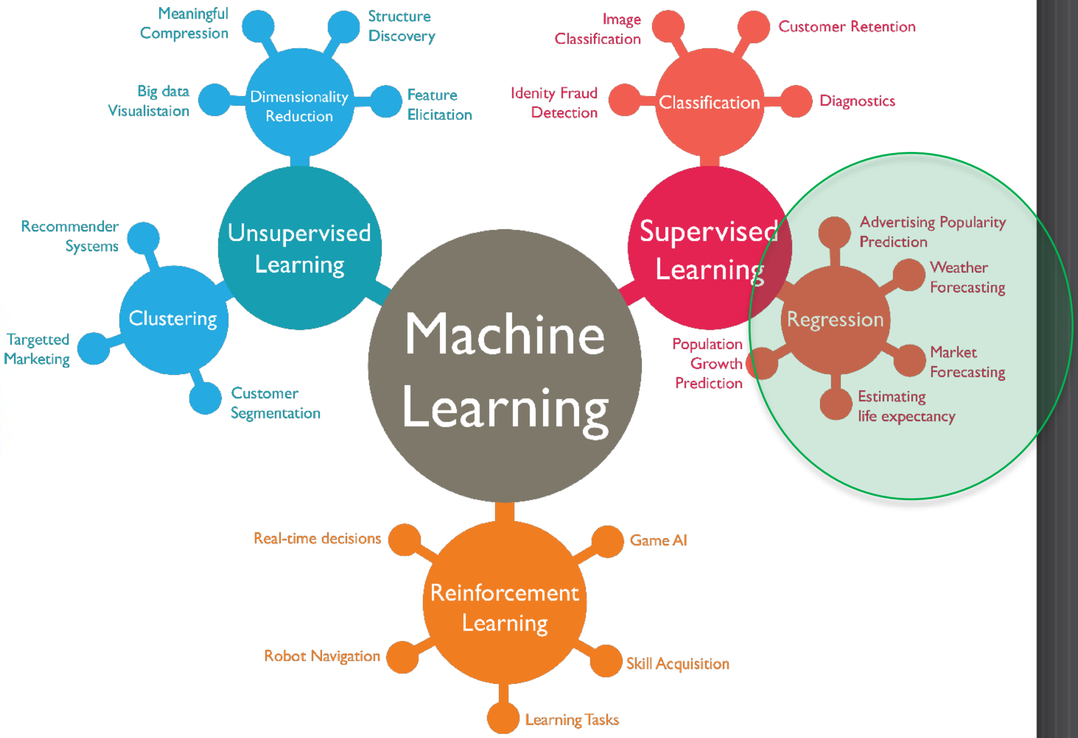
After surface water collection

New AI-Based Tools for Rapid Mix Design

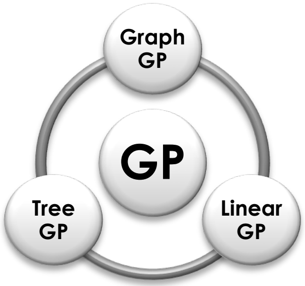
1. **Hamburg Curve Prediction**
2. **DC(T) Curve Prediction**
3. **Other Cracking Tests – Models Under Development (Need More Data)**

Machine Learning?

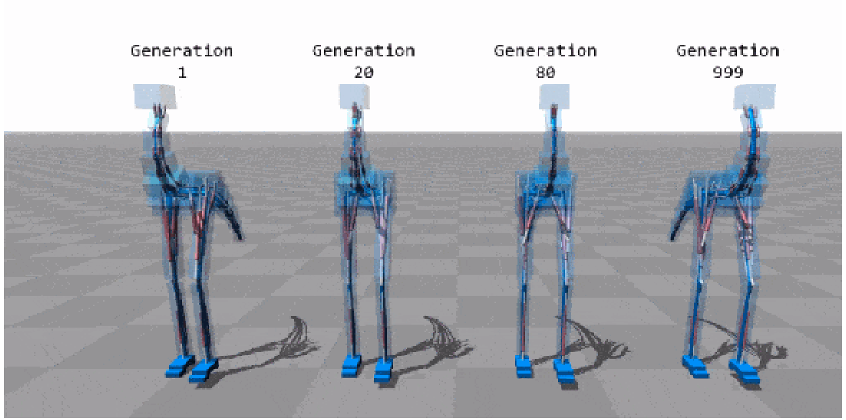




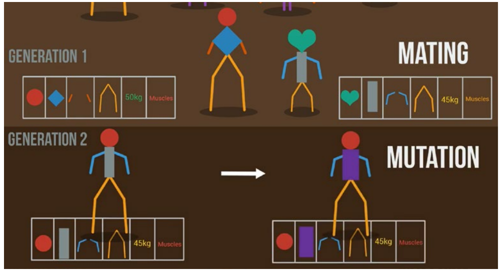
Genetic Algorithm (Evolutionary learning)

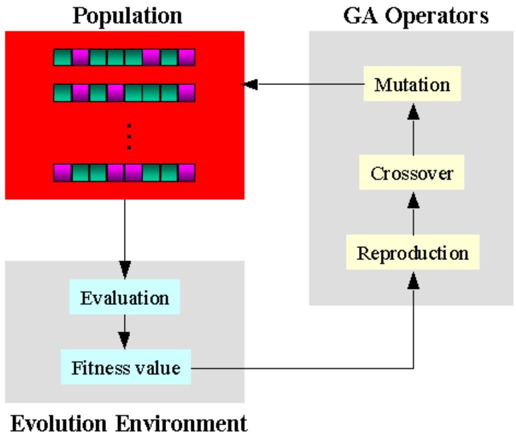


Different types of GP (Alavi and Gandomi 2011)



https://www.r-bloggers.com/feature-selection-using-genetic-algorithms-in-r/



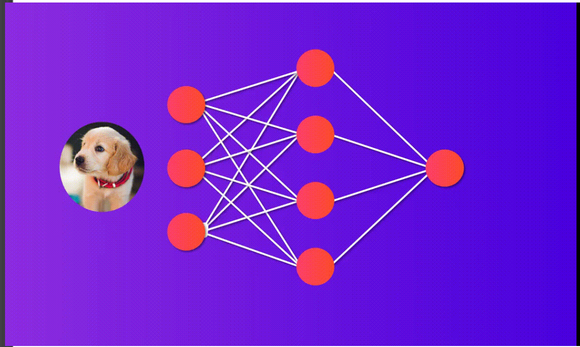


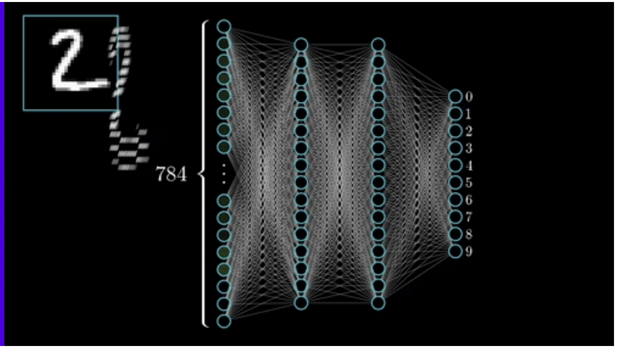
Genetic Algorithm Evolution Flow

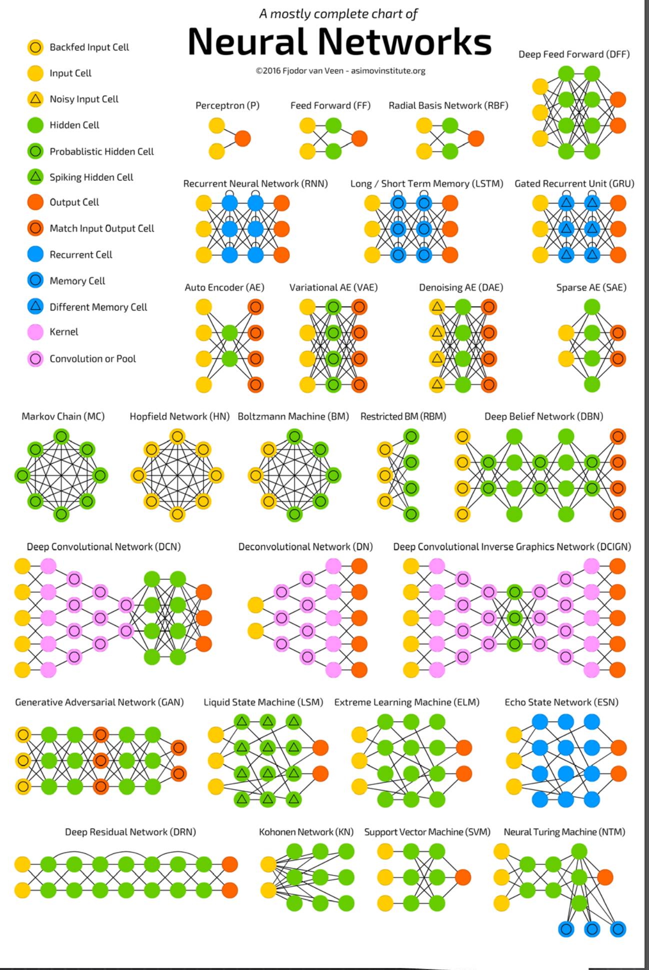
Al-Madi, N. A., & Khader, A. T. (2008)

CNN Structure (Link)

- For large **datasets**, deep learning frameworks can lead to more robust models.
- The **convolutional-neural-network** is a subclass of **neural-networks** which have at least one **convolution layer.**
- They are great for capturing local information (e.g. neighbor pixels in an image or surrounding words in a text) as well as **reducing the complexity** of the model (**faster training, needs fewer samples, reduces the chance of overfitting**).

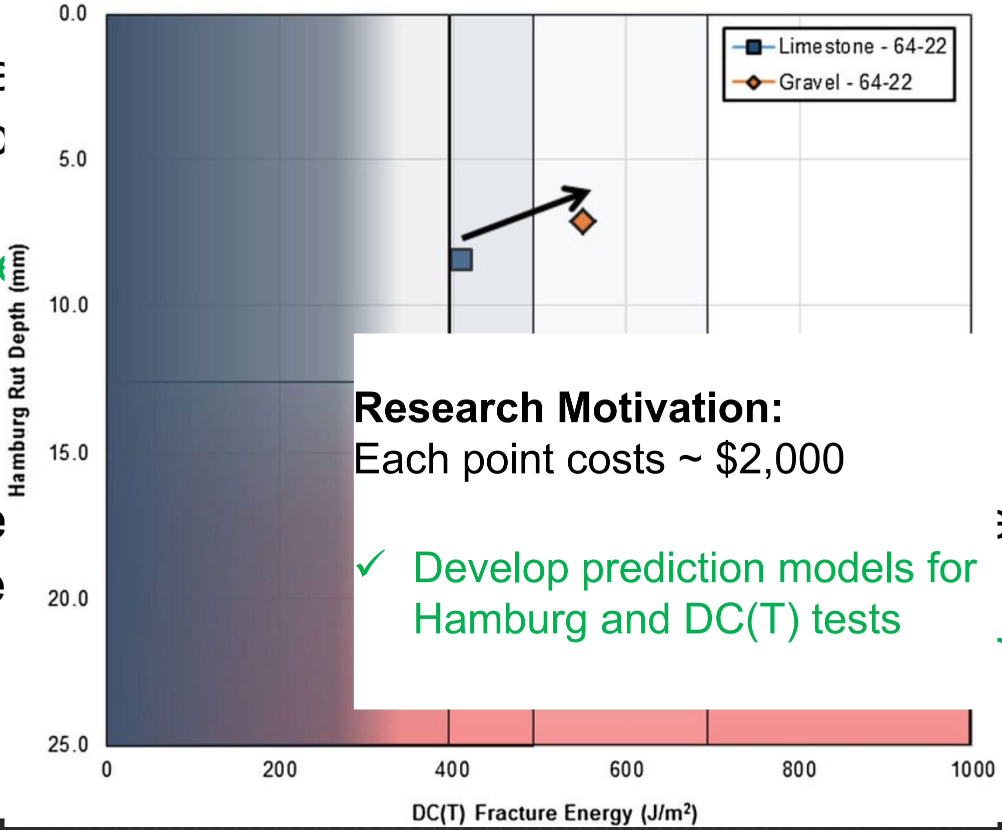






Example 1: Predicting Lab Performance Data

- Developing pre… of asphalt mixtures (numb…
  1. ANN
  2. GEP (Bett…

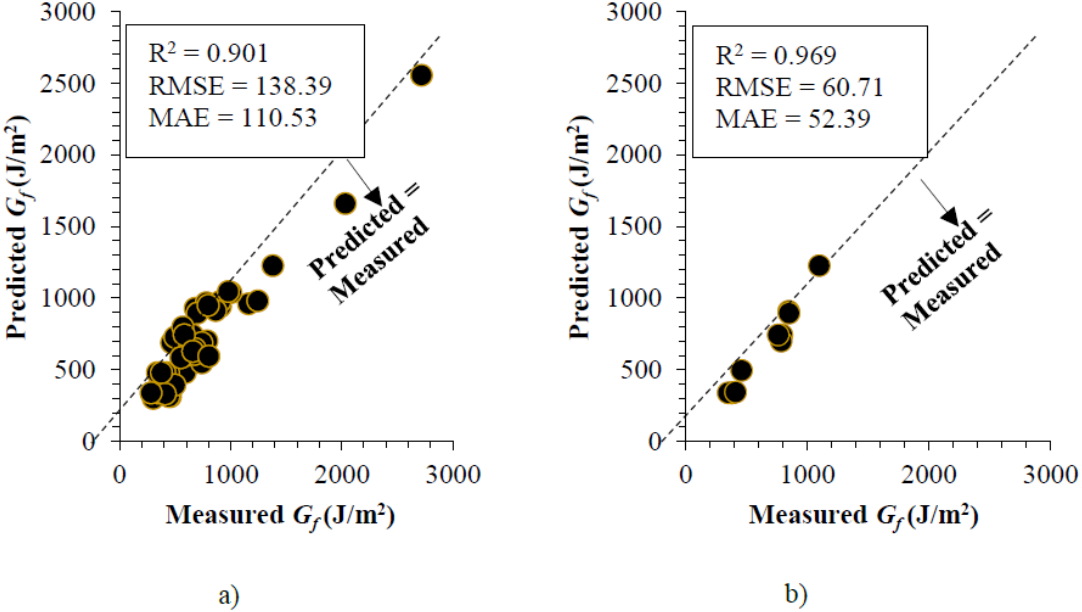


Research Motivation:
Each point costs ~ $2,000

✓ Develop prediction models for Hamburg and DC(T) tests

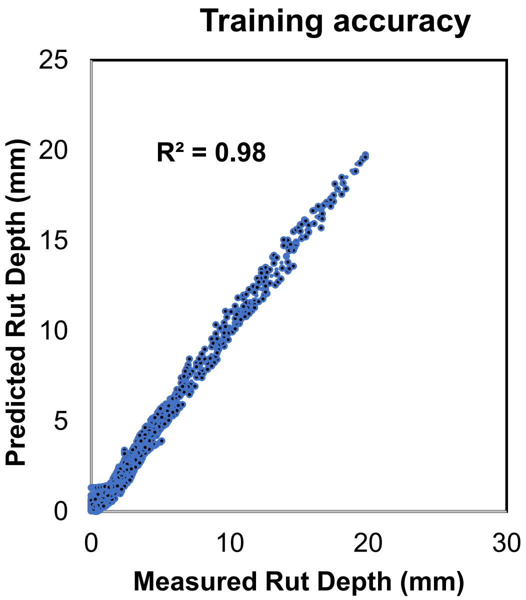
- Developing pre… …eel track) of asphalt mixture…
  1. CNN (deep… …n)
  2. GEP

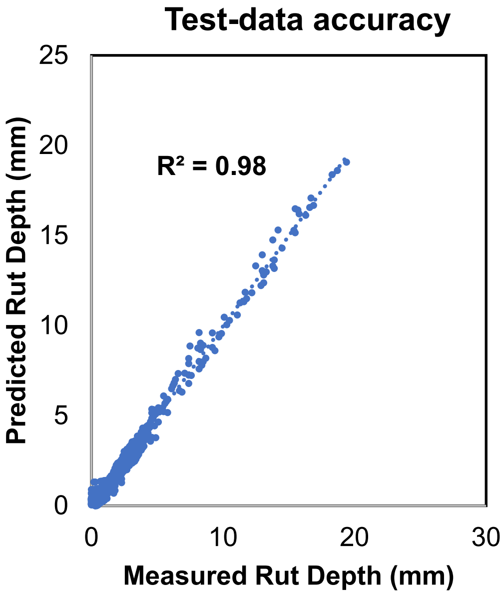
DC(T) Fracture Energy GEP based Model



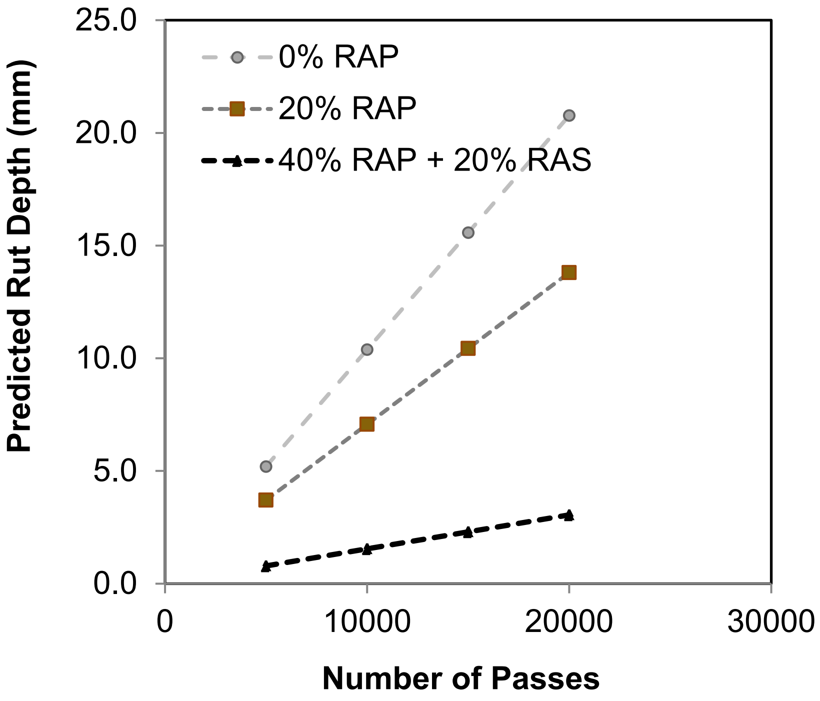
Measured against predicted Gf using the GEP model: (a) training data, (b). 1 testing data

Rutting Prediction CNN-based Model

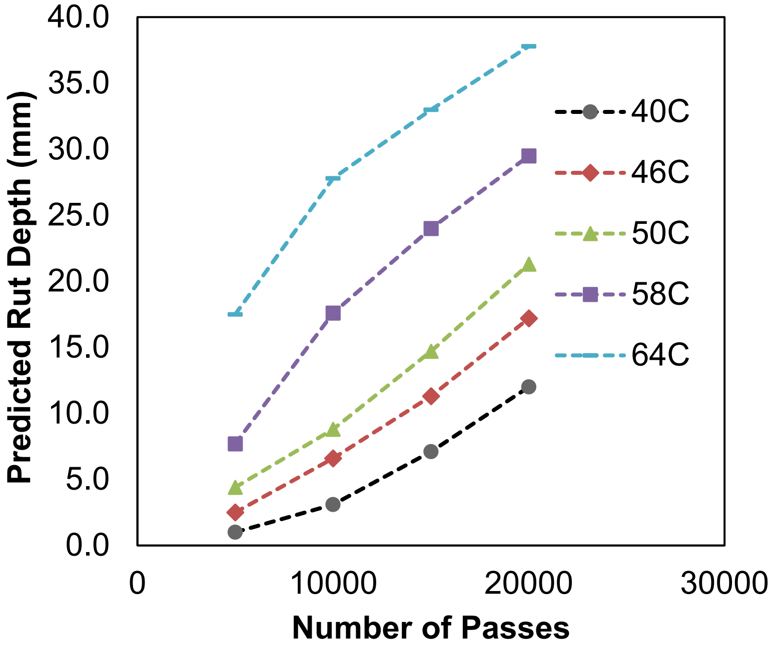




Sensitivity Analysis - Rutting model

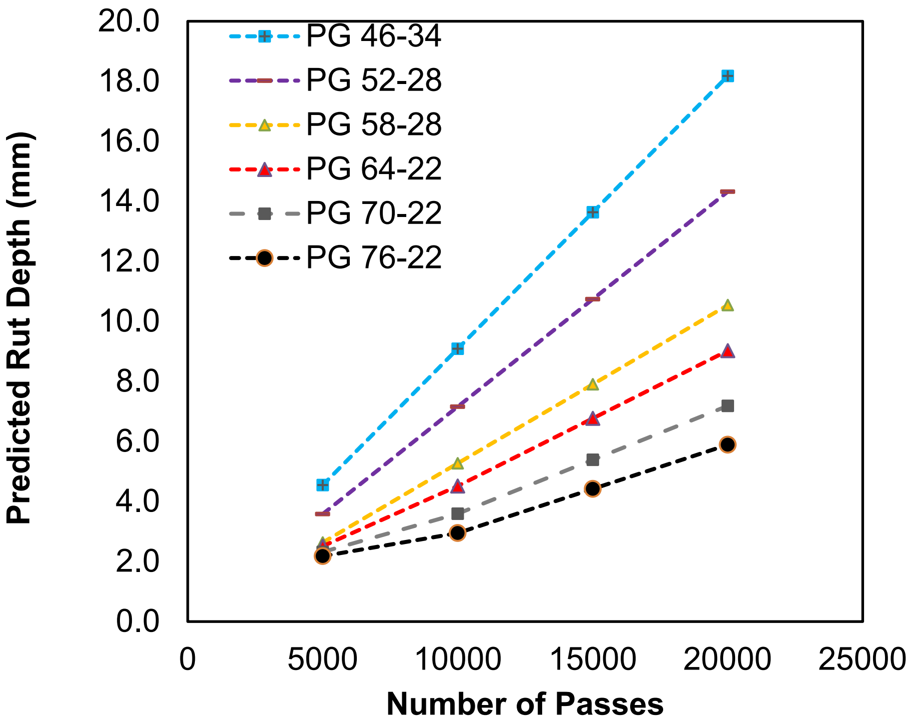


Effect of RAP & RAS

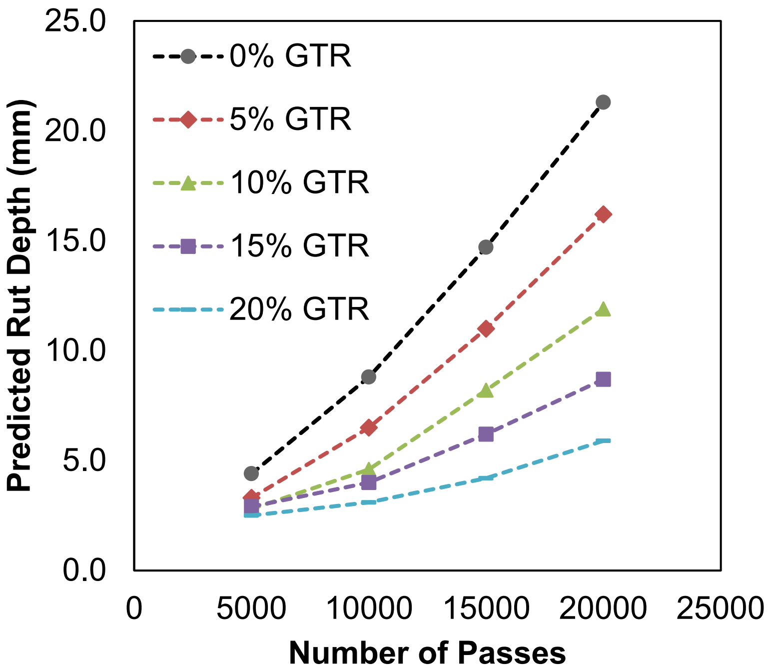


Effect of Test Temp

Sensitivity Analysis - Rutting model (cont.)

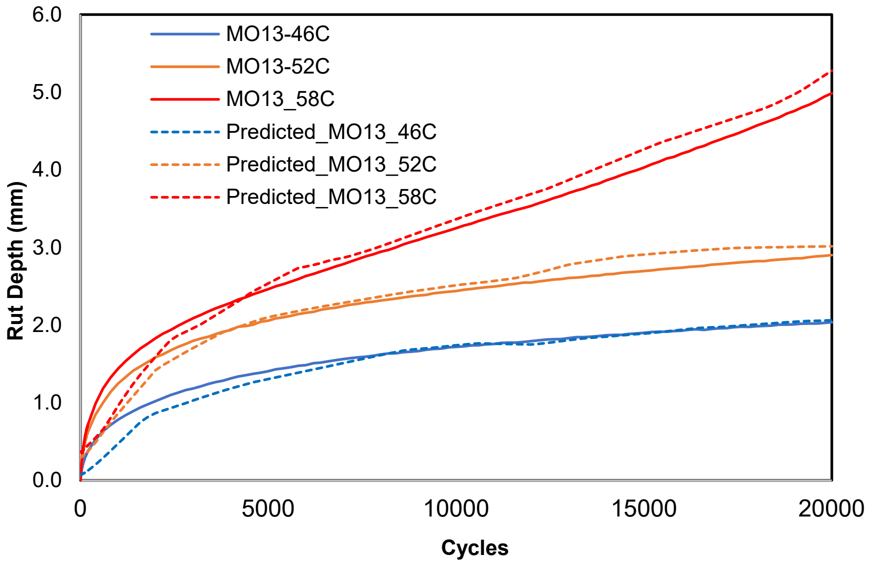


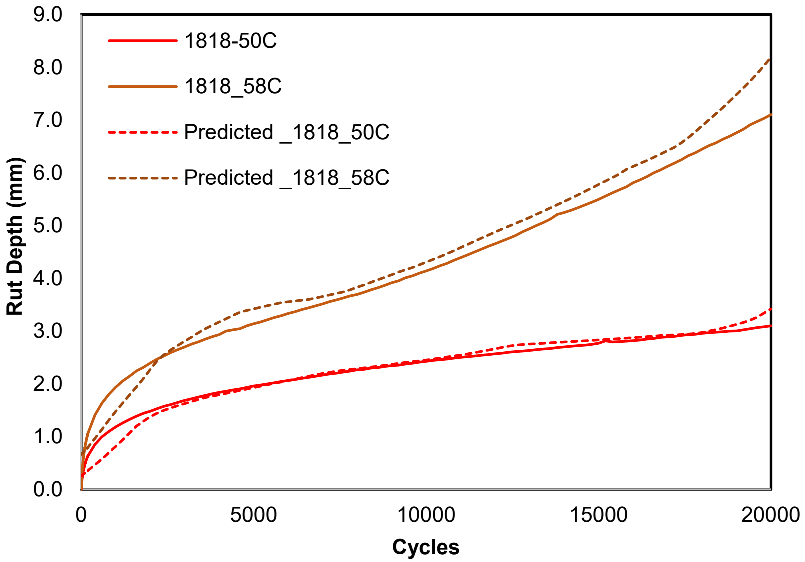
Effect of Binder PG



Effect of Rubber

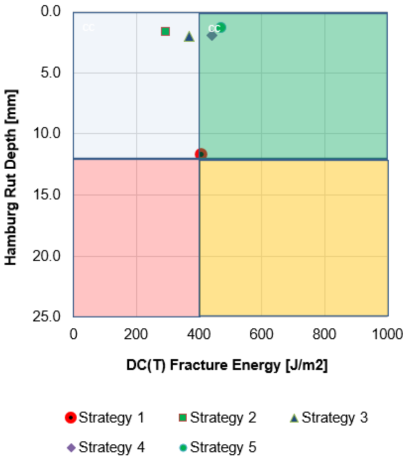
Model Accuracy

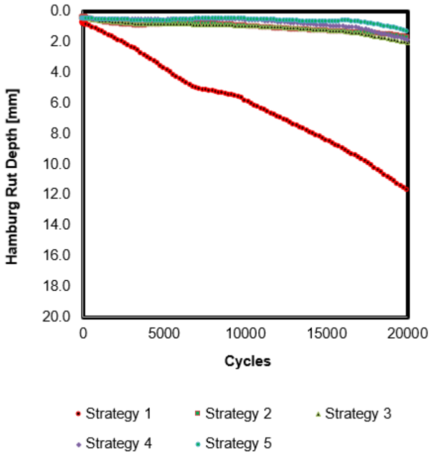




Machine Learning-Based Mix Performance Prediction

	Control	Recycled	Softer binder	Softest binder	Rubber
	Strategy 1	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**
	Virgin Mix + PG 64-22	Recycled Mix + PG 64-22	Recycled Mix + PG 58-28	Recycled Mix + PG 46-34	Recycled Mix + PG 46-34 + 10% Rubber
Parameters					
Mixture Type (Plant: 1; Lab: 2) (Hamburg)	2	2	2	2	2
Virgin Binder Useful Temperature Interval (UTI) (°C)	86	86	86	80	80
Virgin Binder High Temperature Performance Grade (HTPG) (°C)	64	64	58	46	46
Virgin Binder Low Temperature Performance Grade (LTPG) (°C)	-22	-22	-28	-34	-34
Asphalt Content (AC) (%)	5.2	5.2	5.2	5.2	5.4
Total Asphalt Binder Replacement (ABR) (%)	0	40	40	40	40
Nominal Maximum Aggregate Size (NMAS) (mm) (9.5 mm or 12.5 mm)	12.5	12.5	12.5	12.5	12.5
Reclaimed Asphalt Pavement (RAP) (%) (by ABR)	0	20	20	20	20
Reclaimed Asphalt Shingles (RAS) (%) (by ABR)	0	20	20	20	20
Gradation Type (Dense: 1; SMA: 2)	1	1	1	1	1
Aggregate Type (Limestone: 1; Granite: 2)	1	1	1	1	1
Crumb Rubber Content (%) (Hamburg-model)	0	0	0	0	10
Crumb Rubber Content (No Rubber :0, 1:10%Rubber)	0	0	0	0	1
Number of Cycles	20000	20000	20000	20000	20000
Testing Temperature (°C) (Hamburg)	50	50	50	50	50
Testing Temperature (°C) (DC(T) FE)	-12	-12	-12	-12	-12
DC(T) Fracture Energy (j/m^2)	**407.3**	**297.1**	**368.6**	**440.1**	**468.7**
Hamburg Rut Depth (mm)	**11.7**	**1.7**	**2**	**1.9**	**1.3**





Machine Learning-Based Prediction Software

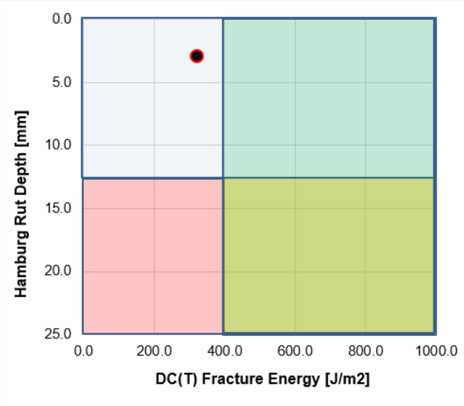
Machine Learning-Based Prediction Model for Perfomance Diagram

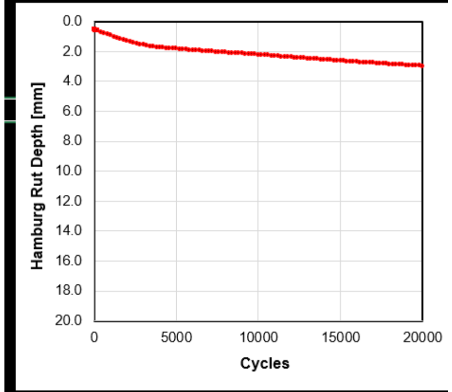
Run

Developed and Designed by:
Majidifard et al., 2020

Parameters	Lower Limit	Upper Limit	Enter Value
Mixture Type (Plant: 1; Lab: 2) (Hamburg)	1	2	2
Useful Temperature Interval (UTI) (°C)	70.00	98.00	86
High Temperature Performance Grade (HTPG) (°C)	46.00	70.00	58
Low Temperature Performance Grade (LTPG) (oC)	-40.00	-22.00	-28
Asphalt Content (AC) (%)	5.10	7.40	5.5
Total Asphalt Binder Replacement (ABR) (%)			40
Nominal Maximum Aggregate Size (NMAS) (mm) (9.5 mm or 12.5 mm)	9.50	12.50	12.5
Reclaimed Asphalt Pavement (RAP) (%) (by ABR)	0.00	35.20	40
Reclaimed Asphalt Shingles (RAS) (%) (by ABR)	0.00	33.50	0
Gradation Type (Dense: 1; SMA: 2)	1	2	1
Aggregate Type (Limestone: 1; Granite: 2)	1	2	1
Crumb Rubber Content (%) (Hamburg)	0	10	0
Crumb Rubber Content (%) (No Rubber :0, 1:10%GTR; 2:10%ECR; 3:10% RMA	0	3	0
Number of Cycles	5000	20000	20000
Testing Temperature (°C) (Hamburg)	40	64	50
Testing Temperature (°C)	-42.00	-12.00	-12

Fracture Energy (j/m^2) =	323.3	Hamburg Rut Depth (mm) =	3.0	OUT of range variable; The result may NOT be reliable!

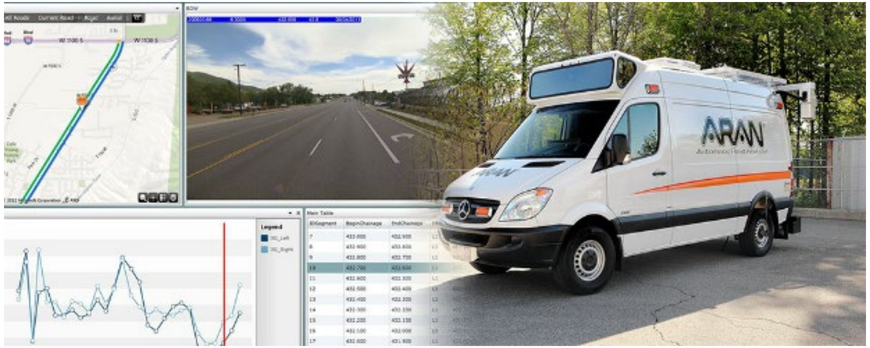




New AI-Based Tools for Rapid Pavement Evaluation

1. **Smart Pavement Monitoring Software**
2. **Cloud-based Annotation Tool**
3. **Data Visualization Software**

Pavement Monitoring



- Traditional method

  -> Sophisticated Data Collection Vehicle (e.g., ARAN)

Cost :

A vehicle equipped with modern sensor and computing systems was purchased by the Ohio Department of Transportation for **US$1,179,000** with an **annual** operating cost **US$70,000** (Vavrik et al., 2013).

Objective of this Study

- Deep Learning Approach for Automatic Pavement Distresses Detection using Google Street view images

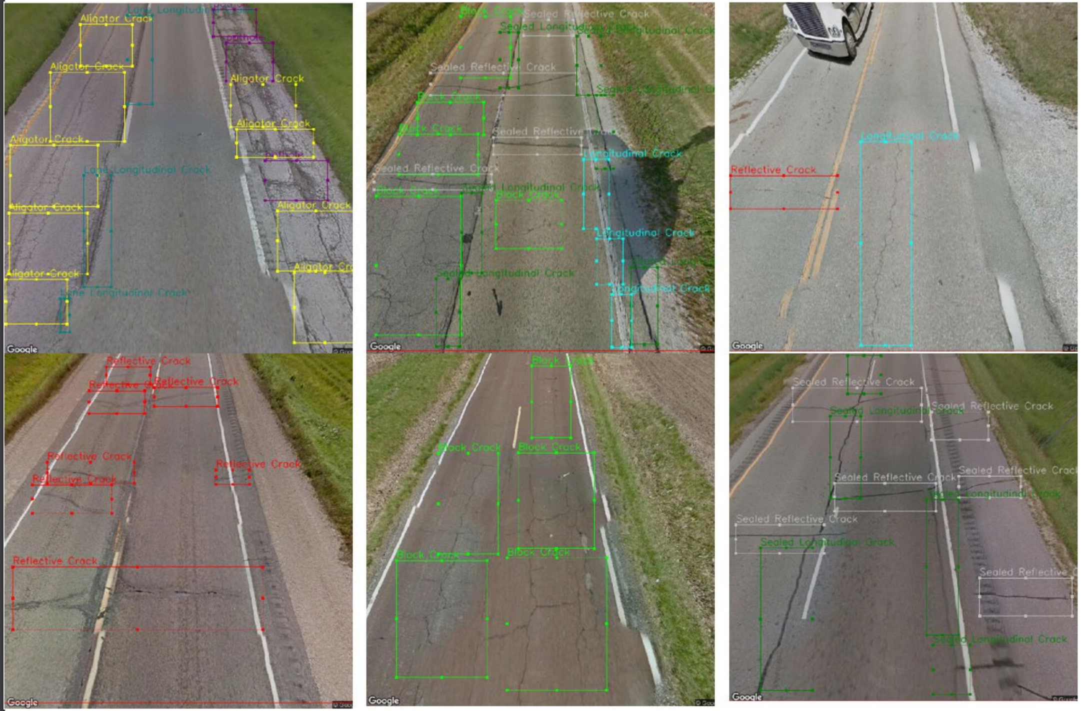
Why Google images? Free/available for virtually every road in the US

Why Automated system?

1) Significant cost savings

2) Excludes human error and bias from the calculation process

Classification of Distresses



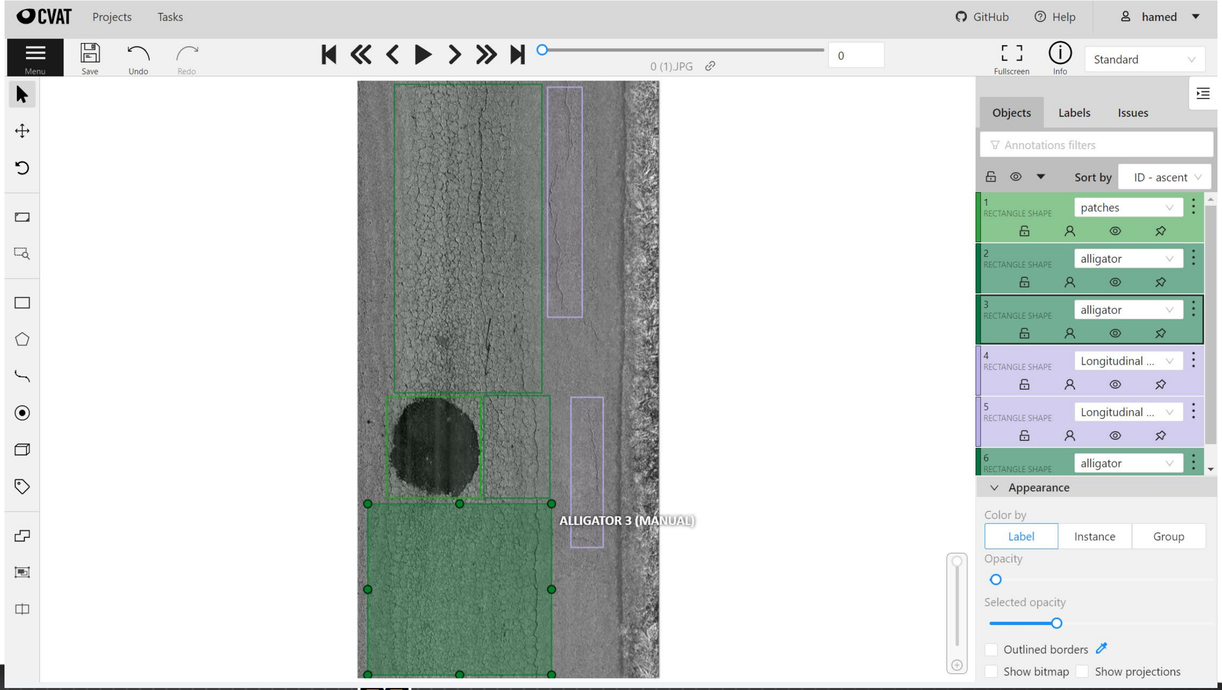
Initially: 7,500 images with nine classes

Table 1. *Distress types versus their corresponding distress ID*

Distress Type	Distress ID
Reflective Crack	D0
Transverse Crack	D1
Block Crack	D2
Longitudinal Crack	D3
Alligator Crack	D4
Sealed Reflective Crack	D5
Lane Longitudinal Crack	D6
Sealed Longitudinal Crack	D7
Pothole	D8

Cloud Annotation Tool

- ✓ Fast, easy, and collaborative image **annotation tool**.
- ✓ More than 10K Images have been annotated so far
- ✓ Local training improves accuracy



Classification Accuracy

NVIDIA GTX 1080Ti GPU used to train the algorithms

Transfer learning was utilized to boost the training speed and performance of the YOLO and Faster R-CNN models

YOLO V2	D0	D1	D2	D3	D4	D5	D6	D7	D8
D0	0.99	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00
D1	0.02	0.97	0.01	0.00	0.00	0.00	0.00	0.00	0.00
D2	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00
D3	0.00	0.00	0.01	0.98	0.00	0.00	0.01	0.00	0.00
D4	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00
D5	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
D6	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00
D7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
D8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

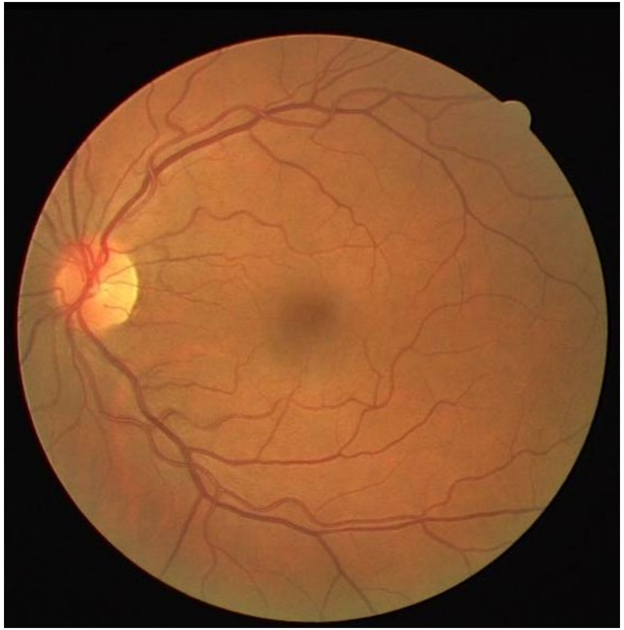
Confusion matrices obtained on the classification dataset using YOLO v2
(Diagonal value ~ 1.00 is best)

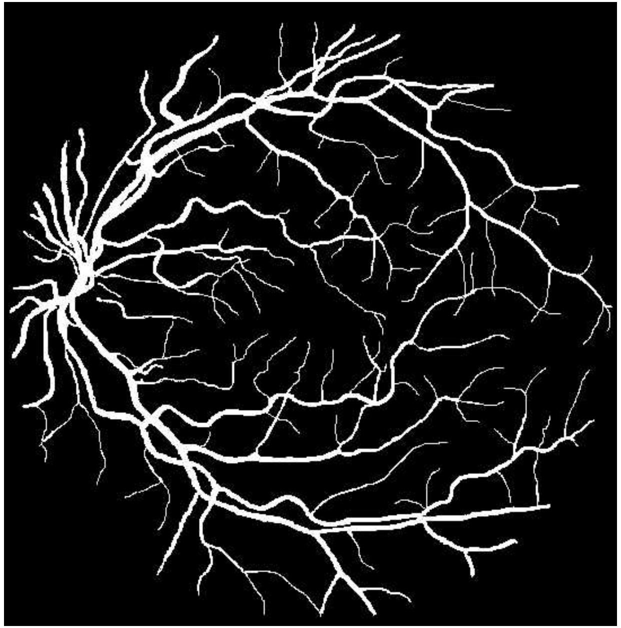
Crack class name	Precision	Recall	F1
Reflective crack	0.93	0.76	0.84
Transverse crack	0.9	0.83	0.86
Block crack	0.93	0.79	0.85
Longitudinal crack	0.91	0.83	0.87
Alligator crack	0.91	0.74	0.82
Sealed transverse crack	0.93	0.83	0.87
Sealed longitudinal crack	0.93	0.79	0.85
Lane longitudinal crack	0.94	0.57	0.71
Pothole	0.96	0.78	0.86
Average	**0.93**	**0.77**	**0.84**

Detection and classification results for nine distress types

U-Net based Model for Distress Quantification

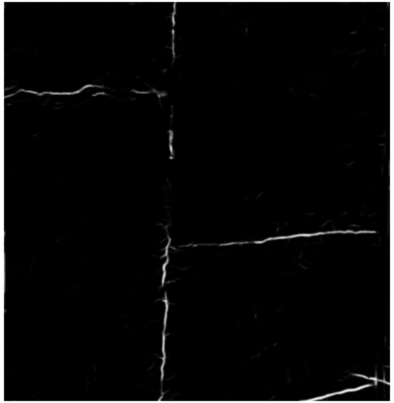
✓ Originally developed for biomedical image segmentation (diabetes detection)





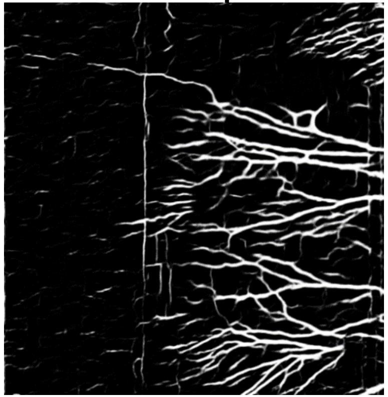
a) Raw Image

b) pre-trained
U-Net output

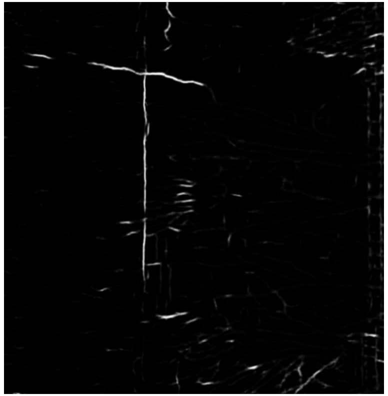


c) Re-trained
U-Net output

a) Raw Image

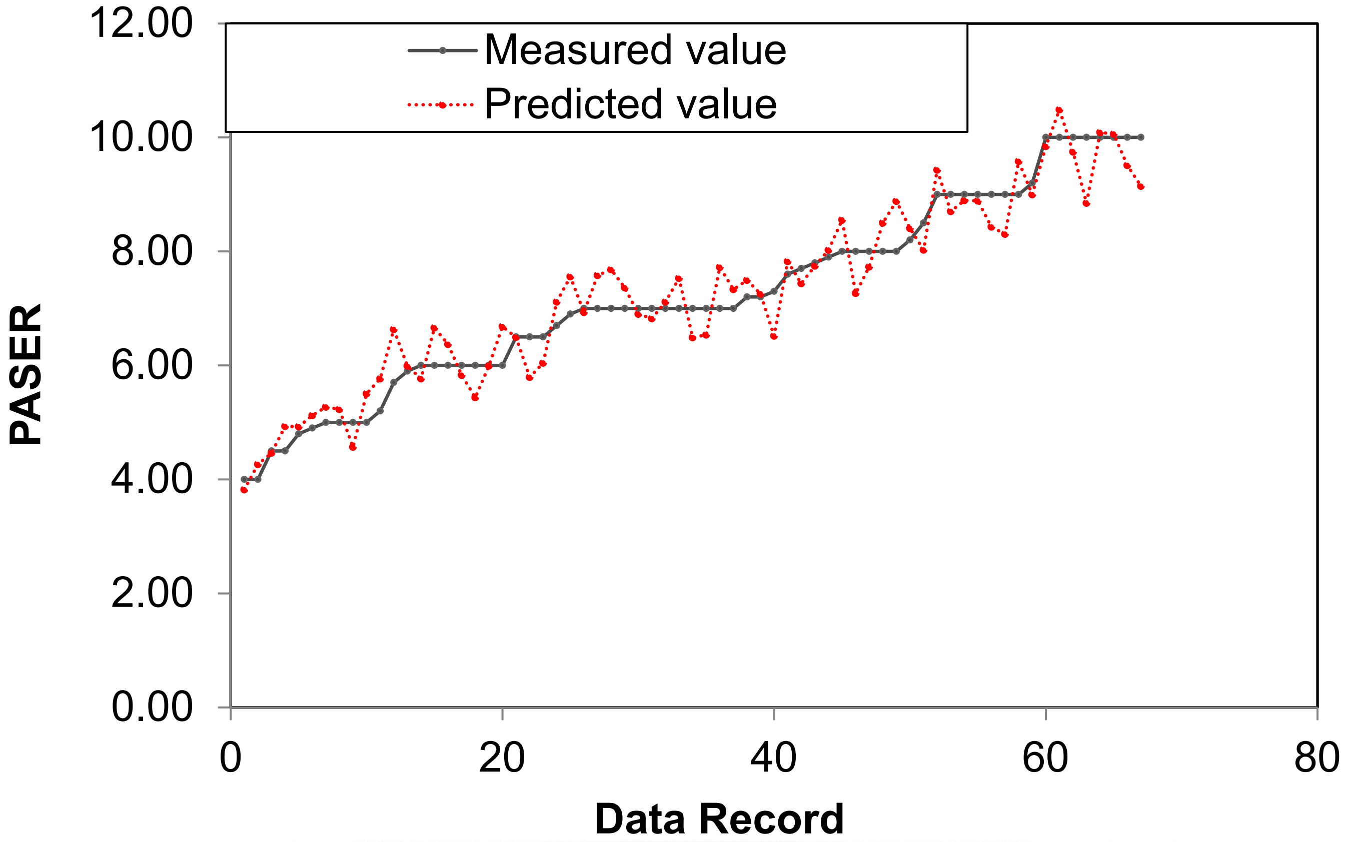


b) pre-trained
U-Net output



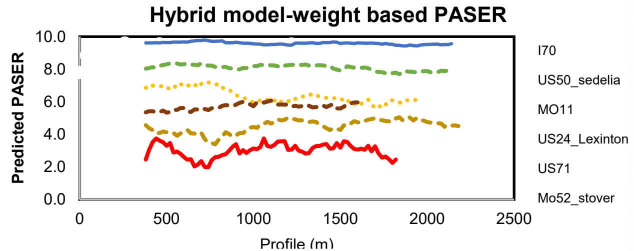
c) Re-trained
U-Net output

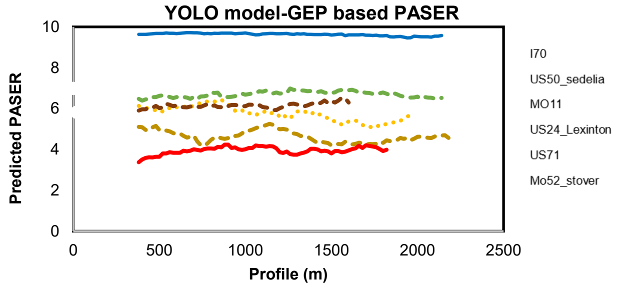
Predicting PASER Rating (YOLO GEP Model)

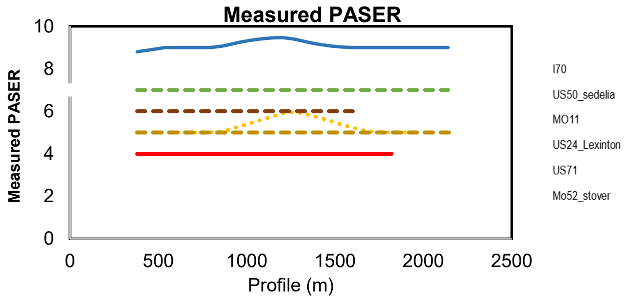


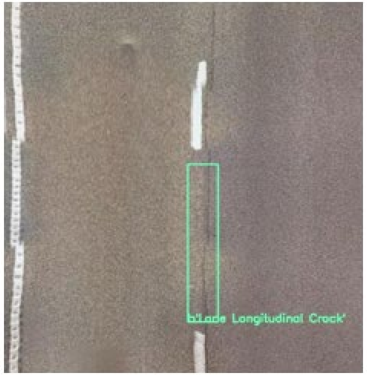
Model Validation

20 per. Mov. Avg. (I70)
20 per. Mov. Avg. (MO11)
20 per. Mov. Avg. (US71)
20 per. Mov. Avg. (US50_sedelia)
20 per. Mov. Avg. (US24_Lexinton)
20 per. Mov. Avg. (Mo52_stover)

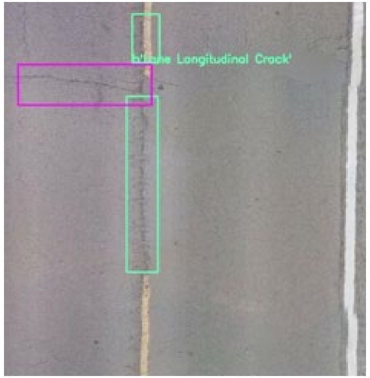




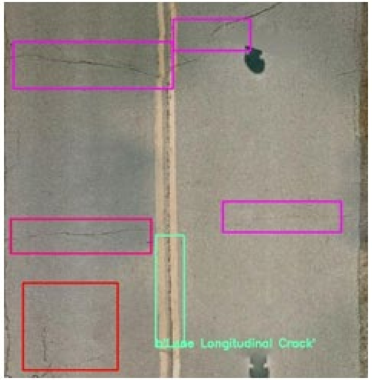




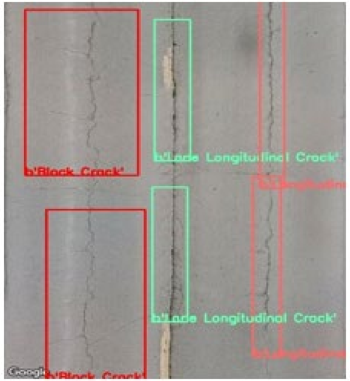
I70



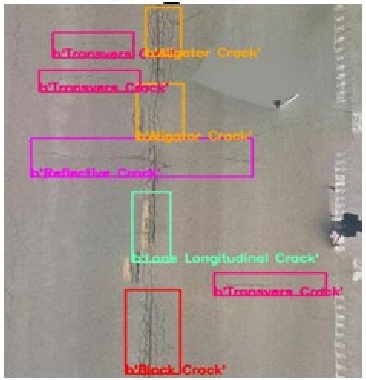
US50_Sedelia



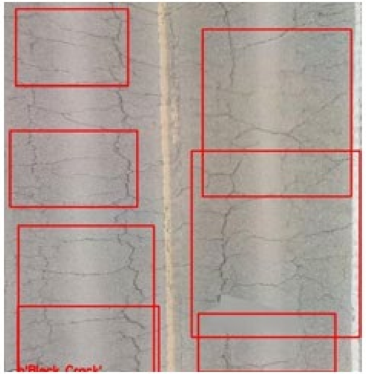
MO11



US24_lexington

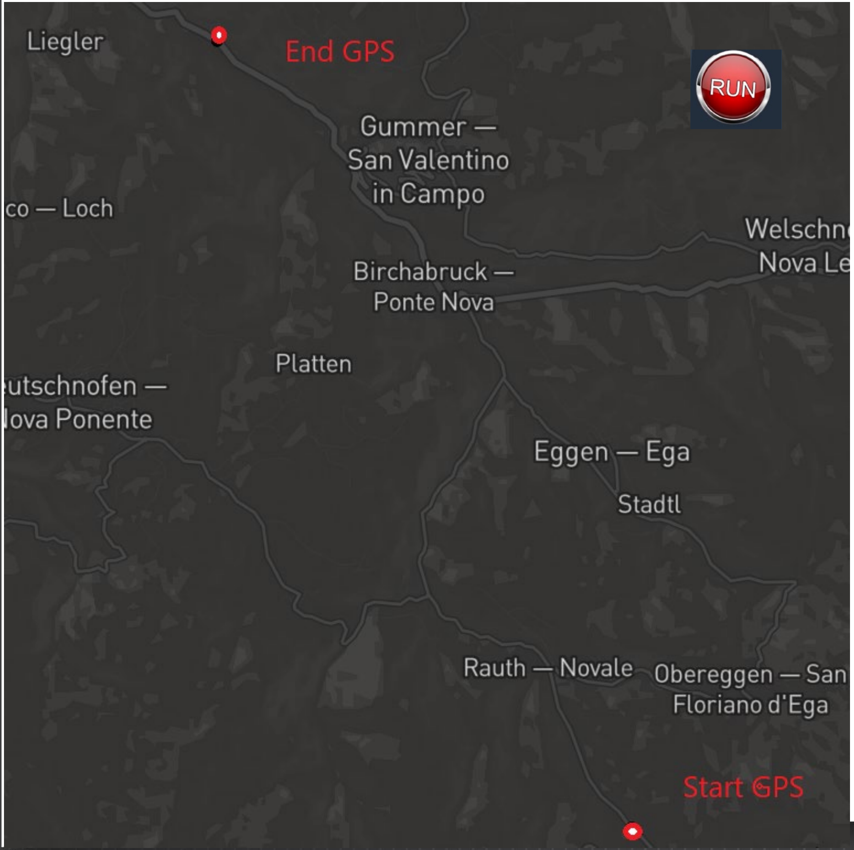


US71



MO52_Stover

Smart Pavement Monitoring Cloud Software



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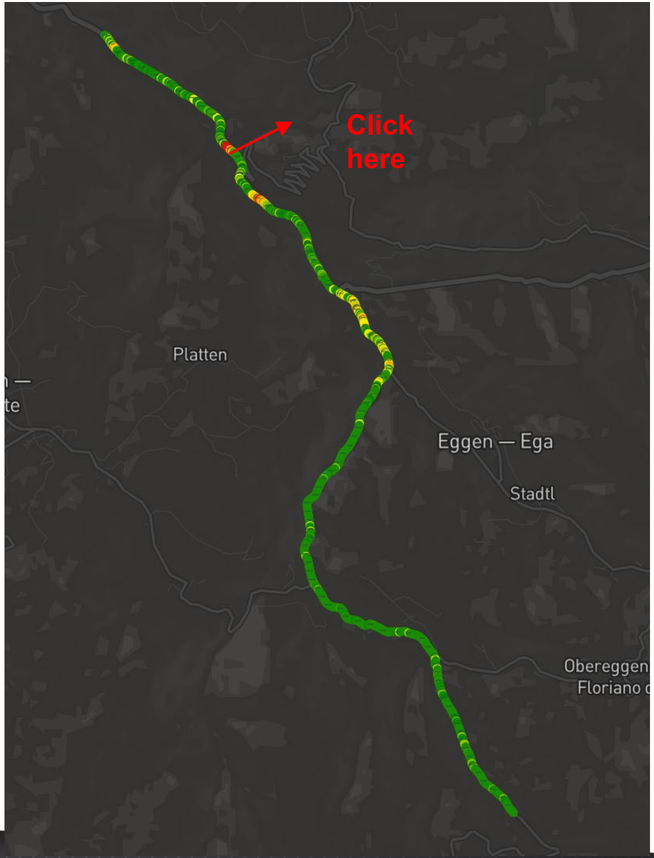
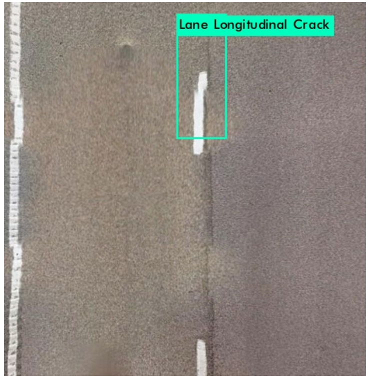


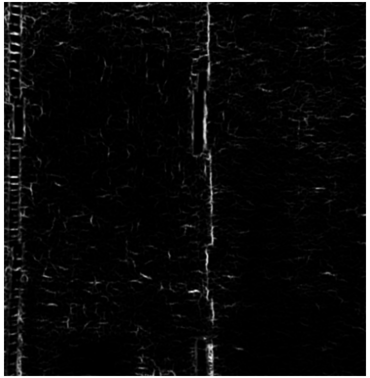
2)

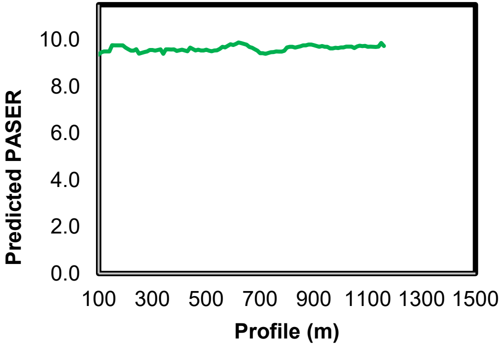
Smart Pavement Monitoring Cloud Software

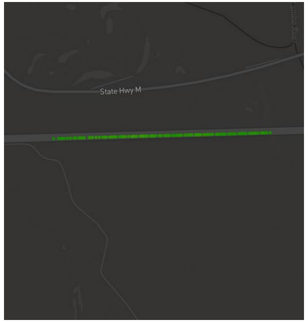
Smart Pavement Monitoring Cloud Software

➢ **Newly Paved Section**



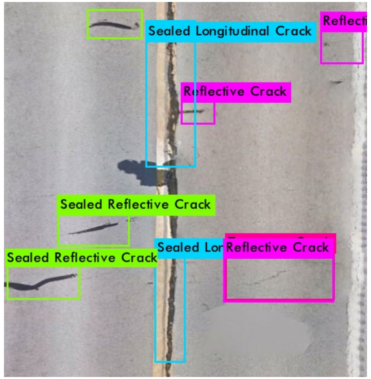


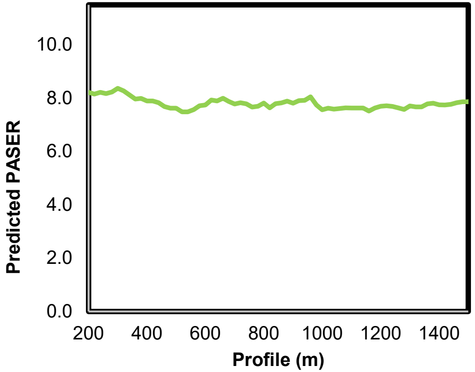


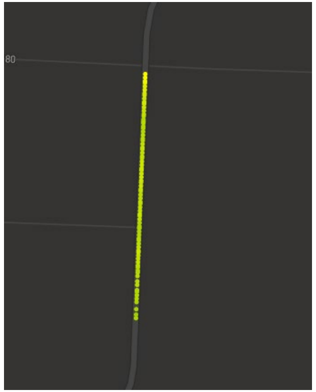


Smart Pavement Monitoring Cloud Software

➢ **Cracked-sealed Section**

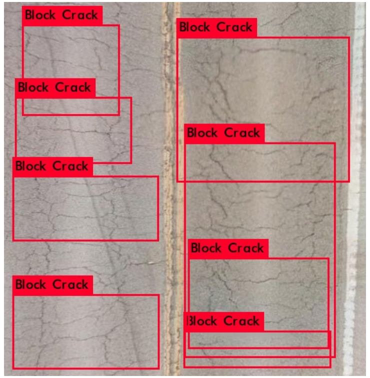


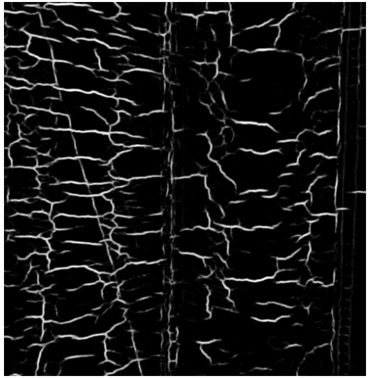


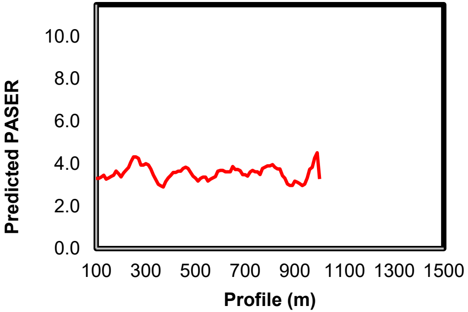


Smart Pavement Monitoring Cloud Software

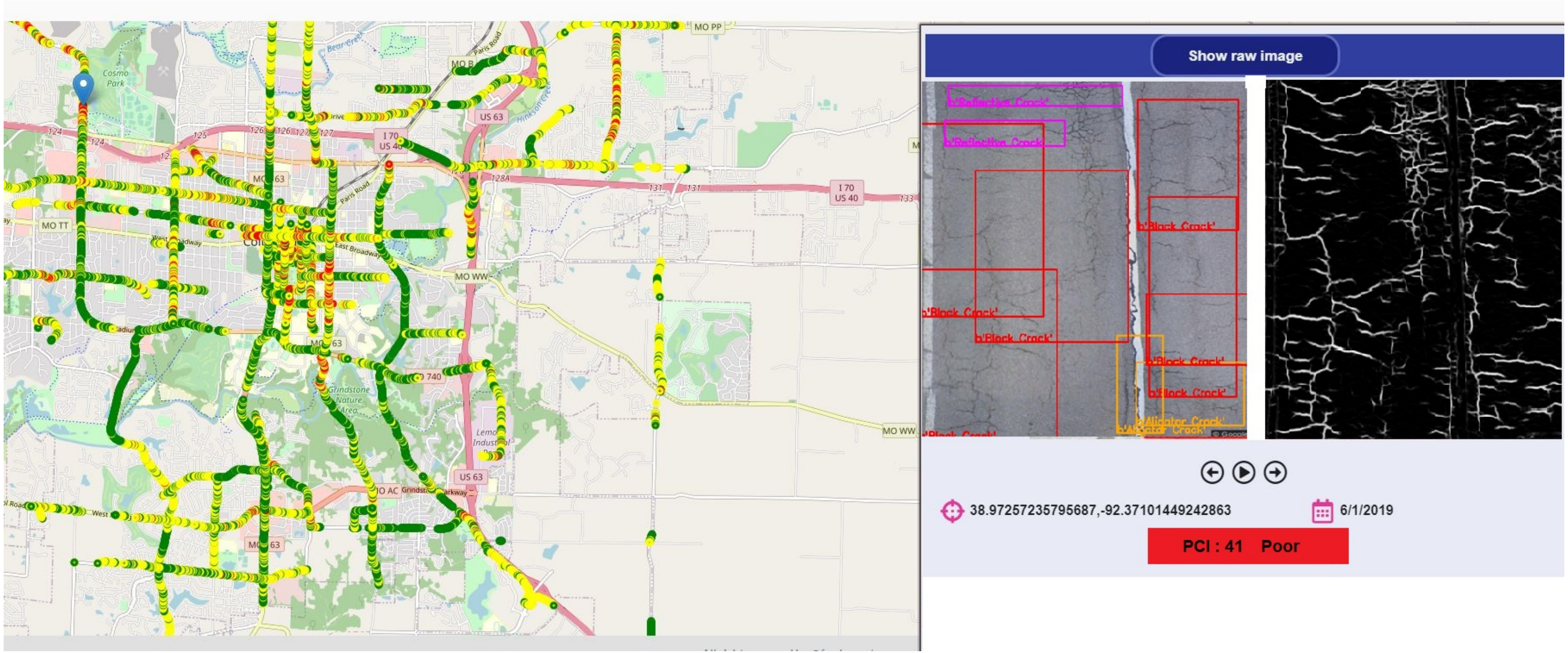
➢ **Dense Block Cracking Section**







Pavement condition visualization map using SPM, Columbia, MO



Ongoing Research in this Area

1. **Updating** the proposed prediction models with **more field data** to produce even more robust models

2. Predicting **rutting** in a more robust manner

3. Developing prediction models for PCI and customizable option to accommodate **other rating systems**, site-specific (**tailored**) rating systems

Data Science for Pavements Symposium

1st International Data Science for Pavements Symposium (DSPS)
Tentative: March 22-24, 2022
Tentative: Turner-Fairbank Highway Research Center, McLean, Virginia, USA

Overview: The Federal Highway Administration (FHWA), in collaboration with the University of Missouri and the University of New Hampshire, is planning an international symposium focused on advancing data science technology in the pavement field. Note that the symposium is still subject to FHWA internal approvals.

Goals: Raise awareness of data science applications and approaches; present spectra of deployment opportunities; identify obstacles to implementation; forge partnerships; chart a path forward for wider scale implementation of data science technology in pavement engineering

Audience: State DOTs, academia (domestic and international), contractors, trade associations

Symposium format: Broadly, the symposium will be split in three sets of activity. The first will offer opportunities for individuals new to data science to learn the basics. The second set will feature cutting-edge research related to data science applications in pavement materials, pavement analysis, pavement management, and asset management. The third set will feature invited presentations from DOTs that have employed data science technology. This session will also include a roundtable of DOTs, contractors, and data science experts to identify gaps and discuss future paths towards an implementation roadmap. A student data competition is being explored through coordination with FHWA's Long-Term Pavement Performance program.

Call for abstracts: A call for abstracts will be submitted in the subject areas identified above (pavement materials, pavement analysis, pavement management, and asset management). A scientific review panel will be identified. The top-rated papers will be invited to submit a full paper for submission to a thematic issue of the Journal of Road Materials and Pavement Design.

Partners: Entities interested in partnering on the symposium development are welcomed at this time.

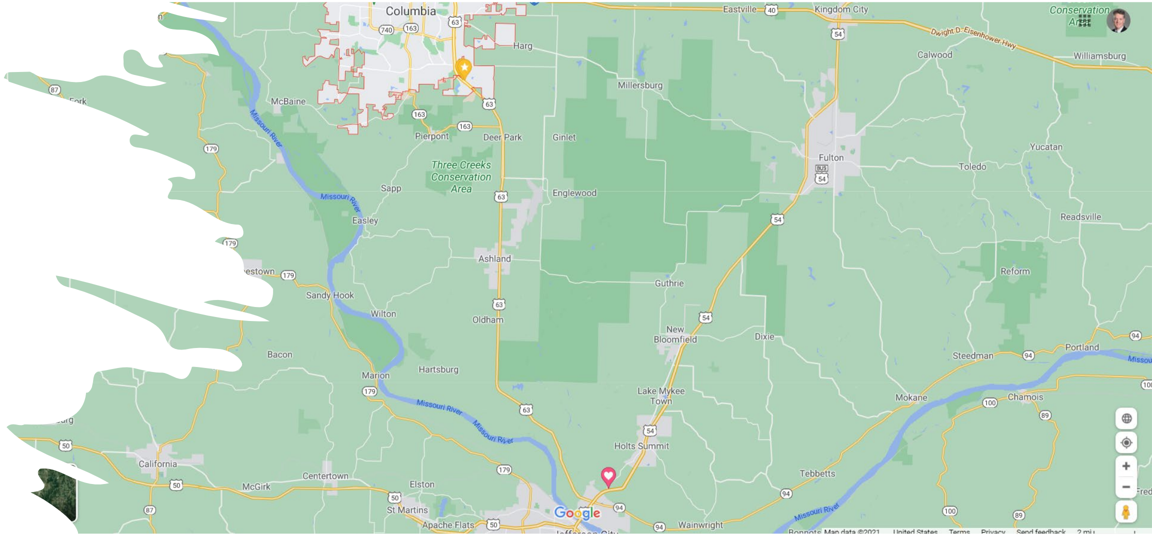
Ongoing/Upcoming Demonstration Projects

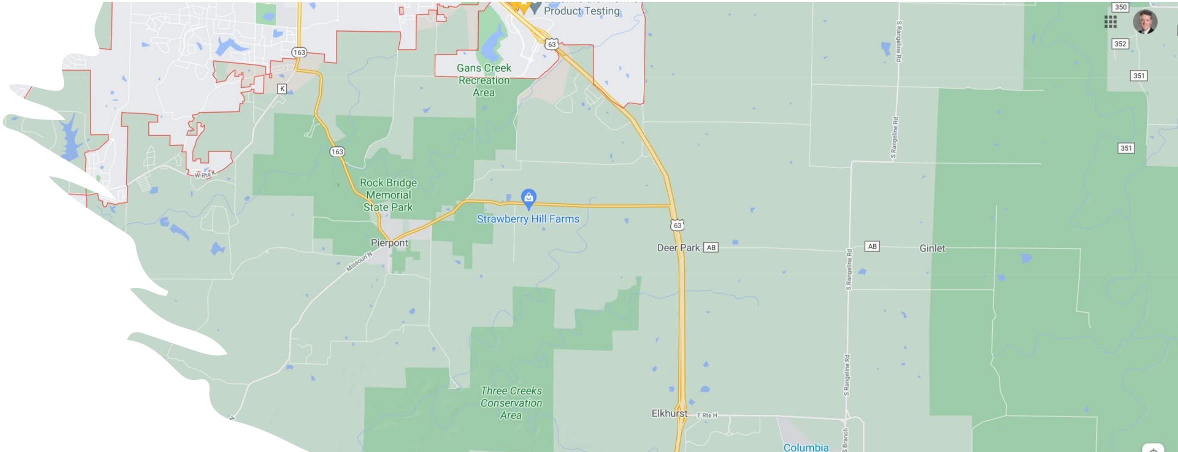
1. **Stadium Blvd., Columbia MO**

2. **US-63**

    - **100-lane miles, Spring 2022**

    - **Launch of Missouri Test Road Network (MTRN), including water quality monitoring at Three Creeks**





Partnership Opportunities

1. **Data Demonstrations/Collaborations – Mix Property Prediction**
2. **Locally Calibrated Software/Predictions – Mix & Pavement Prediction**
3. **Field Demonstration Project Collaborations – Modern Recycling and Associated BMD Specifications, Reflective Crack Mitigation**

Thank you!

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MCTI
MISSOURI CENTER FOR
TRANSPORTATION
INNOVATION
PROPELLING PEOPLE · CONNECTING COMMUNITIES · ENERGIZING ECONOMIES

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