





How Artificial Intelligence is Transforming Transportation Asset Evaluation and Management Bill Buttlar, Hamed Majidifard, Yaw Adu-Gyamfi University of Missouri-Columbia & Tiger Eye Engineering

> TEAM Conference, Branson MO March 14, 2024

# Topics du jour

- Data science in pavements...historical perspective
- Crowd-sourcing, pavement roughness
- Learning and predicting lab performance data
- Assessing field performance



## Pavement Data – 1950's



# Modern Pavement Data Streams **Data Collection** Vehicles rest Roads, ALFs 0 2 2 18 Modern Vehicle Fleet (Moving **Fixed Sensors** Sensors, Crowd Sourcing)



#### Measuring International Roughness Index (IRI) w/ Smartphone





![](_page_4_Picture_3.jpeg)

![](_page_4_Figure_4.jpeg)

Islam, M.S., Buttlar, W.G., Aldunate, R.G., and W.R. Vavrik, "Measurement of Pavement Roughness Using an Android-Based Smartphone Application," TRR 2457 (2014).

Buttlar et al., MoDOT Report, Proj. TR201709, "Pavement Roughness Measurement Using Android Smartphones: Case Study of Missouri Roads and Airports" (2018).

![](_page_4_Picture_7.jpeg)

# **MoDOT Study - Validation**

![](_page_5_Figure_1.jpeg)

\* ARAN-based IRI measurements were taken 2 years earlier. Source: MoDOT's TMS (https://vdi.modot.mo.gov)

![](_page_5_Picture_3.jpeg)

![](_page_6_Picture_0.jpeg)

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# **Mobile App Data Collection**

# **Data Capture:** Store on phone → upload to database later.

- Video
- Accelerations in x, y, z
- Rotations in x, y, z
- Heading
- Speed
- Output:
  - International Roughness Index

![](_page_7_Picture_9.jpeg)

![](_page_7_Picture_10.jpeg)

#### IRI/Condition Crowd-sourcing in Sweden (NIRA, Univrses, Salbo AI, ISI)

100%

Improvement of roads in poor condition

32%

Practical and easy-to-

use decision support tools that make the

process of capital planning transparent, defensible, and

technically robust.

#### **KEY RESULTS**

![](_page_8_Picture_2.jpeg)

Without substantial budget increases, the maintenance deficit on the Swedish road network expects to increase from 19.7 billion SEK in 2020 to 41.8 billion SEK in 2030.

![](_page_8_Picture_4.jpeg)

To further stem its deterioration and maintain the current condition and maintenance deficit of the road network, the maintenance budget would need to increase by 2 billion SEK per year, from an average of 3.4 billion to an average of 5.4 billion per year.

![](_page_8_Figure_6.jpeg)

Map of the expected condition of Sweden's national paved road network in 2030 under the current and recommended budget.

![](_page_8_Figure_8.jpeg)

Solutions

![](_page_8_Picture_9.jpeg)

NIRA Dynamics' core product is its tire pressure indicator; however, NIRA is developing sensor fusion based systems for different vehicle applications. It is working on road surface conditions analysis using data from connected vehicles, RWIS, radar/satellite images and weather prognoses to provide a real-time picture of the road status.

Source: www.worldhighways.com/wh1/news/nira-andunivrses-swedish-road-data-project

#### Machine Learning Is Changing The World

![](_page_9_Picture_1.jpeg)

![](_page_9_Picture_2.jpeg)

![](_page_9_Picture_3.jpeg)

![](_page_9_Picture_4.jpeg)

![](_page_9_Picture_5.jpeg)

## **AI and Machine Learning**

![](_page_10_Figure_1.jpeg)

![](_page_10_Picture_2.jpeg)

#### **Machine Learning in Materials**

Example: Development of a model using an innovative machine learning technique ~ Genetic Programming (GP), to predict the fracture energy of asphalt mixture specimens at low temperatures

![](_page_11_Figure_2.jpeg)

![](_page_11_Picture_3.jpeg)

#### **Our initial GEP-based prediction model**

$$G_f\left(\frac{j}{m^2}\right) = \left(\left(\left(NMAS - 9\right)AT - RAP\right)(5.36 + T - LTPG)\right) - LTPG\right)$$

$$+ AT(G^{4} - 1.7 + UTI) + \frac{NMAS - UTI}{((T + NMAS)AT) - AT + 6.45} - RAS + RAP$$

$$+\frac{LTPG}{AT} + LTPG^2 + 3.49T + AC \times RAP$$

$$+ T\sqrt{CRC^3 - 10T - RAP \times AC - 6.461 + UTI}$$

\* Derived after controlling millions of highly nonlinear models, which is not feasible via other nonlinear regression approaches

![](_page_12_Picture_6.jpeg)

#### Measured vs. Predicted G<sub>f</sub>

![](_page_13_Figure_1.jpeg)

Actually, three portions – Learning (70%), Validation (10%), and Testing (20%). Here we combined Learning and Validation in the figure (both are involved in model selection process).

Majidifard, H., Jahangiri, B., Buttlar, W. G., & Alavi, A. H. (2019). New machine learning-based prediction models for fracture energy of asphalt mixtures. *Measurement*, 135, 438-451.

![](_page_13_Picture_4.jpeg)

#### Hamburg Machine Learning Project @ MAPIL

![](_page_14_Picture_1.jpeg)

	Parameter			
	Chromosomes	20, 30, 50		
	Genes	3, 4, 5		
	Head size	8, 10, 15		
	Linking function	Addition		
General	Function set	+, -, ×, /, $$ , 3, ln, Log, Power, exp, Min, Min 3, Min 4		
	Generation without change	2000		
Complexity increase	Number of tries	3		
	Max. complexity	5		
C	Mutation rate	0.00138, 0.04		
Genetic operator	Inversion rate	0.00546		
	Data type	Floating-poin		
Numerical constants	Lower bound	-10		
		10		

Table 1. Statistical parameters of the dependent and independent variables.

	Mix	UTI	HTPG	AC	ABR	NMAS	RAP	RAS	C	A T	CRC	Т	D	R
	type	(°C)	(°C)	(%)	(%)	(mm)	(%)	(%)	G AI	(%)	(°C)	Passes	(mm)	
Mean	1.1	87.8	58.9	5.9	28.8	11.3	20.9	8.0	1.2	1.2	2.3	52.2	13131	3.8
Median	1.0	86.0	58.0	5.7	32.5	12.5	20.4	0.0	1.0	1.0	0.0	50	10000	2.7
Range	1.0	18.0	24.0	2.8	48.4	14.3	35.3	33.0	1.0	1.0	10.0	24	15000	19.2
Max	2.0	98.0	70.0	7.9	48.4	19.0	35.3	33.0	2.0	2.0	10.0	64	20000	19.7
Min	1.0	80.0	46.0	5.1	0.0	4.8	0.0	0.0	1.0	1.0	0.0	40	5000	0.6

![](_page_14_Picture_5.jpeg)

# **Sensitivity of Variables**

![](_page_15_Figure_1.jpeg)

![](_page_15_Picture_2.jpeg)

#### **Initial Hamburg Machine Learning Model Results**

![](_page_16_Figure_1.jpeg)

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Measured R (mm)

#### **Trends Predicted by Machine Learning Model**

![](_page_17_Figure_1.jpeg)

![](_page_17_Figure_2.jpeg)

Majidifard, H., Jahangiri, B., Rath, P., Contreras, L. U., Buttlar, W. G., & Alavi, A. H. (2021). Developing a prediction model for rutting depth of asphalt mixtures using gene expression programming. *Construction and Building Materials*, 267, 120543.

Majidifard, H., Jahangiri, B., Rath, P., Alavi, A. H., & Buttlar, W. G. (2021). A deep learning approach to predict Hamburg rutting curve. *Road Materials and Pavement Design*, 1-22.

![](_page_17_Picture_5.jpeg)

New Al-Based Tools for Rapid Pavement Evaluation

![](_page_18_Picture_1.jpeg)

![](_page_18_Picture_2.jpeg)

![](_page_18_Picture_3.jpeg)

![](_page_18_Picture_4.jpeg)

![](_page_19_Picture_0.jpeg)

![](_page_19_Picture_1.jpeg)

![](_page_19_Picture_2.jpeg)

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Klionda Strader

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Alixo Shipe

ALEXIS SLUPE

![](_page_19_Picture_13.jpeg)

![](_page_19_Picture_14.jpeg)

#### **Data collection**

Option 1. Using series of high-resolution cameras and Lidar to capture videos in top-down view

![](_page_20_Picture_2.jpeg)

![](_page_20_Picture_3.jpeg)

https://www.blanken shipasphalttech.com /batt-vision

#### **Data collection**

Option 2) Mount phone, camera and/or GoPro to a vehicle to collect wide-view video (can be collected by city/public vehicles)

Perspective correction

Analysis

**TEE cloud** 

![](_page_21_Picture_3.jpeg)

![](_page_21_Picture_4.jpeg)

#### **Prediction Results (Flexible Pavement)**

Representative images and automated distress detection results

![](_page_22_Picture_2.jpeg)

![](_page_22_Picture_3.jpeg)

![](_page_22_Picture_4.jpeg)

#### **Prediction Results (Rigid Pavement)**

Representative images and automated distress detection results

![](_page_23_Figure_2.jpeg)

![](_page_23_Picture_3.jpeg)

#### **IRI Computation – Instructional Video**

https://www.linkedin.com/feed/update/urn:li:activity:7149713049401163776

![](_page_24_Figure_2.jpeg)

![](_page_24_Picture_3.jpeg)

#### **Asset Inventory & Evaluation**

- Curb and gutter evaluation
- Fire hydrant locations
- Garbage can/bin locations (& tags)
- Guardrails, sidewalk inspection
- Sign condition inventory and evaluation
- Pavement marking detection & evaluation
- Utilities, etc...

![](_page_25_Picture_8.jpeg)

![](_page_25_Picture_9.jpeg)

#### **Visualization Dashboard**

![](_page_26_Figure_1.jpeg)

## Sidewalk evaluation

Can quantify faulting, buckling (or blow-ups), and slope variance, including geometrical details of ADA ramps

![](_page_27_Figure_2.jpeg)

# Trail Condition Assessment

![](_page_28_Picture_1.jpeg)

#### **City of Olathe, Trail Inspection**

#### Network size: 40 miles

![](_page_29_Figure_2.jpeg)

![](_page_29_Picture_3.jpeg)

#### Data Collection for Trails/Sidewalks (Via eBike)

![](_page_30_Picture_1.jpeg)

![](_page_30_Figure_2.jpeg)

![](_page_30_Picture_3.jpeg)

Sidewalk surface condition

![](_page_30_Picture_5.jpeg)

**Slope evaluation** 

![](_page_30_Picture_7.jpeg)

**Buckling detection (roughness)** 

![](_page_30_Picture_9.jpeg)

#### Sidewalk Evaluation via eBike

![](_page_31_Picture_1.jpeg)

![](_page_31_Picture_2.jpeg)

![](_page_31_Picture_3.jpeg)

![](_page_31_Picture_4.jpeg)

![](_page_31_Picture_5.jpeg)

![](_page_31_Picture_6.jpeg)

![](_page_31_Picture_7.jpeg)

#### Examples of sidewalk distress/asset detections

![](_page_31_Picture_9.jpeg)

![](_page_31_Picture_10.jpeg)

#### Trail Evaluation, Olathe, KS

![](_page_32_Figure_1.jpeg)

#### **Asset Inventory Demonstration Chicago**

Search Street Here Q

![](_page_33_Figure_2.jpeg)

#### Data-Driven Optimization of Maintenance, Rehabilitation, Sustainable Approaches

- Patching, crack sealing
- Fog seal, chip seal
- Slurry seal, cape seal
- Microsurfacing
- Diamond grinding
- Thin, bonded wearing courses
- Asphalt overlay (thin, thick/structural), BMD
- Reconstruction
- Use of recycled/sustainable materials
- Vetting of trial/experimental materials

![](_page_34_Figure_11.jpeg)

![](_page_34_Picture_12.jpeg)

# Decision Optimization Technology Platform

![](_page_35_Picture_1.jpeg)

- Pavement Management and Optimization Tool, in partnership with Hanson
- Can be added to projects/pilots, when a formal pavement management system is desired (other assets can be managed on the same platform – mixed asset optimization )

![](_page_35_Picture_4.jpeg)

# How AI is Transforming Asset Mgt...

- Machine learning is fast, unbiased, accurate
- Data architectures are cloud-centric, ingest unstructured data, capitalize on data fusion, compatible with GIS/ESRI databases
- Saves time
- Saves \$\$\$
- More data (100% coverage, more frequent inspections, crowd-sourcing possible)
- Easily visualized
- Leads to optimized, mixed-asset management

![](_page_36_Picture_8.jpeg)

#### 3rd International

![](_page_37_Picture_1.jpeg)

Scan QR Code

to Register

![](_page_37_Picture_2.jpeg)

#### March 11 - 14, 2024

Turner-Fairbank Highway Research Center McLean, Virginia, USA

![](_page_37_Picture_5.jpeg)

Workshops & DOT Presentations

![](_page_37_Picture_7.jpeg)

Cutting-Edge Research

#### **HYBRID EVENT**

![](_page_37_Picture_10.jpeg)

![](_page_37_Picture_11.jpeg)

University of New Hampshire

The Federal Highway Administration (FHWA), Missouri Center for Transportation Innovation and the University of New Hampshire invite you to an international symposium focused on advancing data science technology in the pavement field. For more information, visit our website.

![](_page_37_Picture_14.jpeg)

Roundtable & Student Data Competition

![](_page_37_Picture_16.jpeg)

Industry Networking

#### <u>pavementdatascience.com</u>

# Thank you!

# buttlarw@missouri.edu

![](_page_38_Picture_2.jpeg)

# info@tigereye-eng.com

![](_page_38_Picture_4.jpeg)

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#### **References – Al and Machine Learning in Pavements**

- Majidifard, H., Jahangiri, B., Buttlar, W. G., & Alavi, A. H. (2019). New machine learning-based prediction models for fracture energy of asphalt mixtures. *Measurement*, 135, 438-451.
- Majidifard, H., Jahangiri, B., Rath, P., Contreras, L. U., Buttlar, W. G., & Alavi, A. H. (2021). Developing a prediction model for rutting depth of asphalt mixtures using gene expression programming. *Construction and Building Materials*, 267, 120543.
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- Majidifard, H., Jin, P., Adu-Gyamfi, Y., & Buttlar, W. G. (2020). Pavement image datasets: A new benchmark dataset to classify and densify pavement distresses. *Transportation Research Record*, 2674(2), 328-339.
- Majidifard, H., Adu-Gyamfi, Y., & Buttlar, W. G. (2020). Deep machine learning approach to develop a new asphalt pavement condition index. *Construction and building materials*, 247, 118513.

![](_page_40_Picture_6.jpeg)