Modernizing Pavement Management in KY

National Pavement Preservation Conference October 2016 Tracy Nowaczyk, P.E. & Chad Shive, P.E.



PAVEMENT MANAGEMENT FOUNDATION



INVESTMENT IN EQUIPMENT



MODERN PAVEMENT MANAGEMENT DEMANDS



University of Louisville



- Began partnership in fall 2013
- Develop predictive models for asphalt pavement based on legacy data
- Create objective composite pavement distress index
- Map LCMS data to legacy data

Legacy Data

- Visual evaluation system (VES)
- Distresses measured based on overall extent and most common severity
- Year of recommended treatment
- Measured distresses
 - IRI
 - Rutting





Laser Crack Measurement System (LCMS)

- Objective assessment of pavement condition
- Captures more factors
 - High detail of Rutting, Macrotexture, Cracking,
 Potholes, Patches, Sealed Cracks, Vehicle Orientation
 - ~95% accuracy for Longitudinal Cracks, ~90% accuracy for Transverse Cracks
- Shifts needs
 - Much less field time for engineers
 - Some of that times shifts to data processing
 - Once data is processed, entire system can be evaluated

Data Mountain

VES – High level data with low resolution



LCMS – Detailed low level data with high resolution







Need to relate new method to legacy data

					WPC	WPC					OS	OS	
	RT UNIQUE	FROM	TO	LANE	JD	JD	R F	RF	OC	OC	Р	Р	
	ID	POINT	POINT	DIR	EXT	SEV	EXT	SEV	EXT	SEV	EXT	SEV	APP
	122-KY-9000	0	3.648	L	9	7	5	5	5	5	0	0	3
	122-KY-9000	3.648	11.913	L	6	5	3	4	5	2	3	1	3
	122-KY-9000	11.913	16.02	L	3	1	2	2	1	1	0	0	1
From	122-KY-9000	16.02	19.15	L	3	1	1	1	1	1	0	0	1
	122-KY-9000	19.15	22.307	L	1	1	0	0	1	1	0	0	0.5

То

					CWBS	CWBS	CWBS	CWBS	
Section Name	Begin	End	LEN	DIP	TypA	TypA	TypA	TypA	
Session Name	MP	MP	(mile)	DIK	Sev	Low	Med	High	
					(in)	(ft)	(ft)	(ft)	
15-KY-1494N	6.6	6.7	0.1	N	0.690	89.383	62.992	15.632	
15-KY-1494N	6.7	6.8	0.1	Ν	0.426	154.435	130.666	3.121	
15-KY-1494N	6.8	6.9	0.1	Ν	0.421	199.566	140.278	3.534	
15-KY-1494N	6.9	7	0.1	Ν	0.544	256.281	371.720	23.269	
15-KY-1494N	7	7.1	0.1	Ν	0.458	134.963	89.799	4.914	

DPPC16

Too Much Data!!!

LCMS reports 176 fields, where do we start?

- Leading Factors Identification for each visual index
- Clustering Analysis (Verifying data integrity / Outlier detection)
- Factorial Analysis (Significance testing for regressor variables)
- Principal Component Analysis (exploratory)
- Regression Modeling
 - Linear Regression
 - **Ordinal Logistic Regression**

Formal Approach

- Step 1: Factors Identification
- Step 2: Data Consolidation and Preprocessing
- Step 3: Data Quality Check
- Step 4: Factorial Analysis using Analysis of Variance (ANOVA)
- Step 5: Linear Regression Model for Data Mapping

Factor Identification

Wheel Path Cracking Extent	Wheel Path Cracking Extent Wheel Path Cracking		Other Cracking Extent (OC [®])
(WPC ^e)	Severity (WPC ^s)	Appearance (AFF)	Other Cracking Extent (OC)
Fatigue Type A EXT	Fatigue Type A SEV	Fatigue Type A SEV	Edge Crack EXT
Fatigue Type A LOW	Fatigue Type B SEV	Fatigue Type B SEV	Edge Crack LOW
Fatigue Type A MED	Fatigue Type C SEV	Fatigue Type C SEV	Edge Crack MED
Fatigue Type A HIGH	Fatigue Type D SEV	Fatigue Type D SEV	Edge Crack HIGH
Fatigue Type B EXT	Non WP Long SEV	Non WP Longitudinal SEV	Transverse Crack EXT
Fatigue Type B Area EXT		Edge Crack SEV	Transverse Crack LOW
Fatigue Type C EXT		Transverse Crack SEV	Transverse Crack MED
Fatigue Type C Area EXT		Sealed Crk Fatigue A LENGTH	Transverse Crack HIGH
Fatigue Type D EXT		Sealed Crk Long LENGTH	Transverse Crack Count LOW
Fatigue Type D Area EXT		Sealed Crk Edge Length	Transverse Crack Count MED
Non WP Longitudinal EXT		Sealed Crk Transverse Length	Transverse Crack Count HIGH
Non WP Longitudinal LOW		Sealed Crk Transverse Count	Unclassified Crack LOW
Non WP Longitudinal MED		Sealed Crk Unclassified Length	Unclassified Crack MED
Non WP Longitudinal HIGH			Unclassified Crack HIGH
Sealed Crk Fatigue A LENGTH			Unclassified Crack Count LOW
Sealed Crk Long LENGTH			Unclassified Crack Count MED
			Unclassified Crack Count HIGH
			Sealed Crk Edge Length
			Sealed Crk Transverse Length
			Sealed Crk Transverse Count
			Sealed Crk Unclassified Length



Data Consolidation and Preprocessing

- Summarize LCMS data for each VES segment
 - Two methods, Average & Max
 - Average method uses length weighted average for all LCMS values that cover a VES section
 - Max method uses maximum LCMS value within a VES section
- Use additional factors from LCMS data
 - Weighted Cracking Extent
 - Pattern Density

Data Quality Check

- Clustering Analysis
 - Agglomerative Hierarchical Clustering
 - All samples start as separate individual clusters
 - Build hierarchy from individual elements by progressively merging the clusters
 - Based on desired distance level (dk), user can choose set of clusters

Data Quality Check

		Dendrogram Ward Linkage, Euclidean Distance														
WPC	TypeA Ext	TypeA Weighted Ext	TypeA Low	TypeA Med	TypeA High	TypeB Ext	TypeB Area Ext	TypeB Patt Den	TypeC Ext	TypeC Area Ext	TypeC Patt Den	NWP LONG EXT	NWP LONG Weighted EXT	NWP LONG LOW	NWP LONG MED	NWP LONG HIGH
0	0.40	0.61	0.23	0.12	0.05	0	0	0	0	0	0	13.66	16.18	11.16	2.47	0.03
0	0.29	0.39	0.21	0.06	0.02	0	0	0	0	0	0	116.24	142.11	90.67	25.26	0.30
0	0.78	0.93	0.63	0.15	0	0	0	0	0	0	0	78.40	94.76	62.22	15.99	0.19
0	12.11	14.34	9.92	2.15	0.04	1.85	3.33	0.00	0	0	0	58.28	73.35	43.46	14.56	0.26
0	2.56	4.34	1.46	0.42	0.68	0	0	0	0	0	0	139.20	178.61	100.96	37.09	1.16
0	46.47	55.23	37.72	8.73	0.02	191.1	137.21	0.02	13.31	6.39	0.01	440.61	598.24	283.75	156.09	0.77
								c	Observa	ations			1	1	6	5

Factorial Analysis



- Fit various combinations of the LCMS input variables to the VES output variable and study the Analysis of Variance (ANOVA) results to determine the significant and non-significant factors
- Low p-value (<0.05) is desired for any factor to be significant in the model
- The R2 value shows how close the data is fitted to the regression line
- Sequentially remove factors with large p-values from the model until all factors are significant

Factorial Analysis

Analusia of Vanianas

Analysis of variance								
Source	DF	Adj SS	Adj MS	AFTER SELECTING MAJOR CON	NTRIBUTING	FACTORS	FROM ABO	VE ANALYSIS
Regression	12	236.649	19.7207					
Fat_Crk_TypeA_Low	1	0.528	0.5280	Analysis of Variance				
Fat_Crk_TypeA_Med	1	6.471	6.4714					
Fat_Crk_TypeA_High	1	8.740	8.7405	Source	DF Adj SS	Adj MS	F-Value	P-Value
Fat_Crk_TypeB_Ext	1	18.701	18.7009	Regression	6 222.78	37.129	17.44	0.000
Fat Crk TypeB Area Ext	1	15.013	15.0126	Fat_Crk_TypeA_Med	1 11.84	11.841	5.56	0.023
TypeB PattDen	1	7.062	7.0624	Fat_Crk_TypeA_High	1 23.77	23.771	11.16	0.002
Fat Crk TypeC Ext	1	0.405	0.4052	Fat_Crk_TypeB_Ext	1 39.37	39.366	18.49	0.000
Fat Crk TypeC Area Ext	1	1.556	1.5561	Fat_Crk_TypeB_Area_Ext	1 27.19	27.195	12.77	0.001
TypeC PattDen	1	2.703	2.7027	TypeB_PattDen	1 30.51	30.514	14.33	0.000
NON WHEEL LONG LOW	1	5.205	5.2046	Non_WP_LONG_Weighted_EXT	1 45.19	45.194	21.23	0.000
NON WHEEL LONG MED	1	1.247	1.2467	Error	42 89.43	2.129		
NON WHEEL LONG HIGH	1	16.209	16.2086	Total	48 312.20	8		
Error	36	75.555	2.0988					
Total	48	312.204		Model Summary				
Model Summary				S R-sq R-sq(adj)	R-sq(pred)			
				1.45919 71.36% 67.26%	60.62%	6.1		
S R-sq R-sq(adj) F	-sq(pred)						
1.44871 75.80% 67.73	8	0.00%		Regression Equation				
				WPC_JD_EXT = 1.192 - 0.0589	Fat_Crk_Ty	peA_Med		

WPC_JD_EXT = 1.349 + 0.0100 Fat_Crk_TypeA_Low = 0.(+ 1.054 Fat_Crk_TypeA_High = 0.0646 Fat_Crk_TypeB_Ext + 0.926 Fat_Crk_TypeA_High = 0.0522 Fat_Crk_TypeB i + 0.0600 Fat_Crk_TypeB_Area_Ext + 144.5 TypeB_PattDen

+ 0.0510 Fat Crk TypeB Area Ext + 98.0 TypeB Pattle + 0.00512 Non WP LONG Weighted EXT

- 0.0204 Fat Crk TypeC Ext + 0.090 Fat Crk TypeC Area Ext

- 261 TypeC_PattDen + 0.00498 NON_WHEEL_LONG_LOW

+ 0.00450 NON_WHEEL_LONG_MED + 0.0734 NON_WHEEL_LONG_HIGH

Better model fit but less terms are significant

Factorial Analysis

AFTER SELECTING MAJOR	CON	TRIBUTING	FACTORS	FROM ABOVE ANALYSIS
Analysis of Variance				AFTER SELECTING MAJOR CONTRIBUTING FACTORS FROM ABOVE ANALYSIS
Source	DF	Adj SS	Adj MS	F-V Analysis of Variance
Regression	3	155.084	51.695	2
Fat_Crk_TypeB_Sev	1	15.739	15.739	Source DF Adi SS Adi MS E-Value P-Value
Fat_Crk_TypeC_Sev	1	19.013	19.013	$\frac{1}{2}$ Regression 2 173 08 86 538 63 63 0 000
NON_WHEEL_LONG_SEV	1	7.839	7.839	Fat Crk TypeB Sev 1 20.97 20.970 15.42 0.000
Error	45	80.549	1.790	NON WHEEL LONG SEV 1 12.95 12.948 9.52 0.003
Total	48	235.633		Error 46 62.56 1.360
Model Summary				Total 48 235.63
S R-sq R-sq 1.33790 <mark>65.82% 6</mark>	(adj <mark>3.54</mark>) R-sq(p <mark>% 55</mark>	red) .48%	Model Summary
Regression Equation WPC_JD_SEV = 0.141 +	1.70	3 Fat_Crk	_TypeB_Se	S R-sq R-sq(adj) R-sq(pred) 1.16616 <mark>73.45% 72.30% 68.39%</mark> ev +
+ 0.955	NON_	WHEEL_LON	G_SEV	Regression Equation
				WPC JD SEV = -0.753 + 8.78 Fat Crk TypeB Sev + 5.93 NON WHEEL LONG SEV

Factorial Analysis

	AVG n	nethod	MAX method		
VES Indices	No. of Significant Factors	Model Fit (Adj R²)	No. of Significant Factors	Model Fit (Adj R²)	
Wheel Path Cracking Extent (WPC_EXT)	6 /16	67.26 %	2 / 16	<mark>66.06 %</mark>	
Wheel Path Cracking Severity (WPC_SEV)	2/4	72.30 %	3/4	63.54 %	
Other Cracking Extent (OC_EXT)	7 / 10	65.35 %	3 / 10	57.63 %	
Other Cracking Severity (OC_SEV)	1/1	74.23 %	1/1	39.54 %	
Raveling Extent (R_F_EXT)	4/5	70.39 %	3/5	57.37 %	
Appearance (APP)	1/5	43.52 %	2/5	54.09 %	
National Paveme	nt Preserv	vation Con	ference 20	016	

Next Steps

- Larger data samples
 - Entire dataset of 2015/2016 testing
- Ordinal logistic regression to model dependent variables as Integer values (for the visual indices)
- Use of Clustering analysis to develop separate regression models for various clusters
 - Different models for newer (less distressed) pavements vs older

Path to Prioritization

Collect pavement condition data in the past planning cycle

Run regression models to predict distress indices

Perform AHP analysis for weights for criteria

Calculate composite condition index for all road segments

Rank all projects based on composite condition index



Existing Project Prioritization

- Composite pavement scores derived from distress indices
- Large emphasis on roughness of the road
- Projects prioritized based on roughness instead of pavement deterioration

Analytic Hierarchy Process

- Structured Technique for organizing complex decisions
- Based on mathematics and psychology
- Interviews with panel of experts
- Weights for individual indices calculated and validated
- Each project receives single overall priority score

Composite Pavement Distress IndexPairwise comparison

	WPC_E	XT	5	RF_EXT	1				
INTENSITY OF IMPORTANCE		DEF	INIT	ION					
1		"fac	tor	A" and "facto	or B" are equally i	mportant			
3		"factor A" is moderately favored than "factor B"							
5	"factor A" is strongly favored than "factor B"								
7			"factor A" is very strongly favored than "factor B"						
9		"fac	tor /	A" is extreme	ely favored than "	factor B"			
2,4,6,8		Rati	ngs	are between	two adjacent juc	lgements			
	ational	Pave	eme	ent Preserv	ation Conferen	ce 2016			



Pavement Distress Index (PDI)

- Matrix exercise produced new set of weightings
- New system provides 0-1 scale for each section
- Pilot study comparison of prioritization projects
- Successfully addressed the overemphasis of IRI



Future PMS Map



Special Thanks

- Dr. Lihui Bai
- Dr. Zhihui Sun
- Guanyang xu
- Prajwal khadgi
- Peiyu luo