The Application of Backpropogation Neural Network to deal with randomness of the Pavement Performance Modeling

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ABSTRACT

The objective of this study is to apply the Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm for offsetting the statistical errors of the pavement performance modeling. The Multi-Layer Perceptron (MLP) network and sigmoid activation function are applied to build the BPN network. Collector and arterial roads of both flexible and rigid pavements in Montreal City are taken as a case study. Data on pavement condition and age, traffic volume and road characteristics are collected from Ville de Montréal. The input variables of Pavement Condition Index (PCI) are Average Annual Daily Traffic (AADT), Equivalent Single Axle Loads (ESALs), Structural Number (SN), pavement's age, slab thickness and difference of PCI between current and preceding year (∆PCI). The BPN networks estimates that the PCI has inverse relationships with AADT, ESALs and pavement's age. The PCI has positive relationships with these variables for roads that have recent treatment operations. The PCI has positive relationships with SN and slab thickness that imply that the increase of structural strength and slab thickness increases the pavement condition. The ∆PCI significantly influences the estimation of PCI values. The AADT and ESALs have considerable importance, however, pavement's age and structural characteristics of pavement have insignificant influence in determining the PCI values except in the case of flexible arterial roads.

INTRODUCTION

Pavement performance curves are to ensure the accuracy of pavement maintenance and rehabilitation (M&R) operations (Attoh-Okine 1999).

Two streams of pavement performance modeling - deterministic and stochastic approaches.

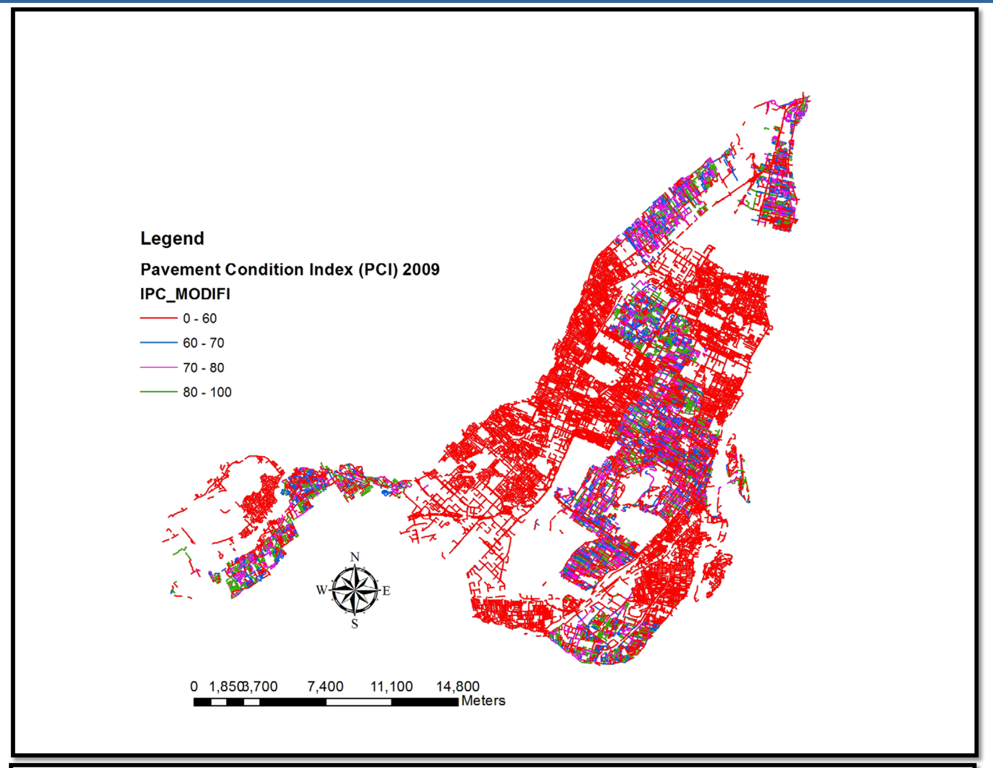
Deterministic models cannot address some important issues such as (a) randomness of traffic loads and environmental conditions, (b) difficulties in quantifying the factors or parameters that substantially affect pavement deterioration, (c) measurement errors associated with pavement condition and (d) bias from subjective evaluations of pavement condition (Li et al. 1997).

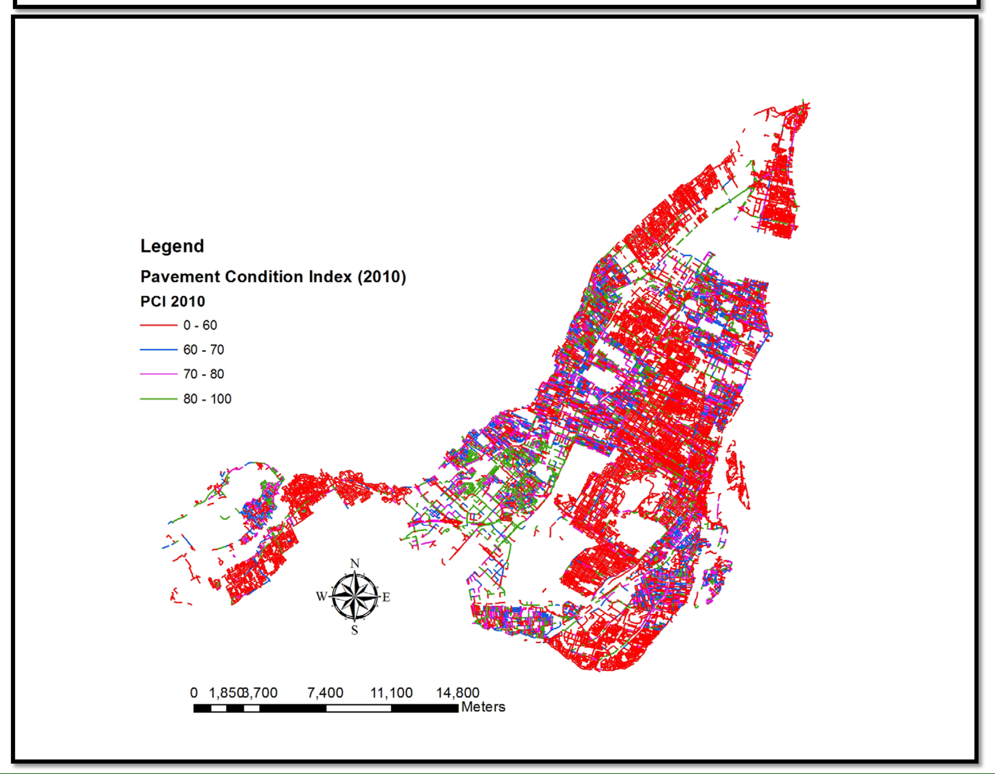
Stochastic models (a) do not accommodate budget constraints along with condition state and (b) pavement sections are grouped into a small number of roughly homogeneous families

Objective:
To apply Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm to offset the statistical error of the pavement performance modeling.

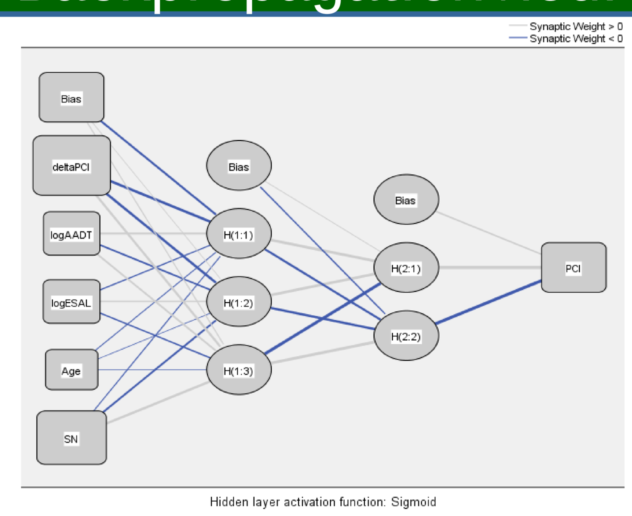
Collector and arterial roads of Montreal City are taken as a case study.

Pavement Condition Index (PCI) Montreal Road Network- Case Study

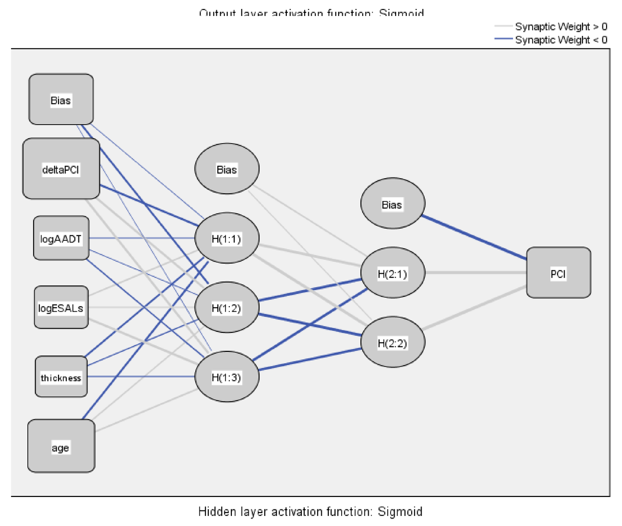




Methodology Backpropagation Neural Network (BPN)



BPN network diagram for flexible pavement



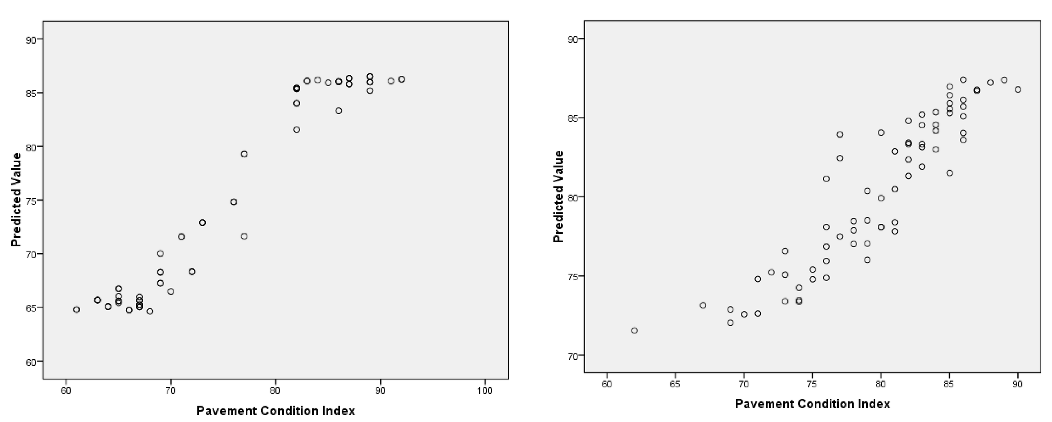
BPN network diagram for rigid pavement

Back Propagation Neural Network Performance

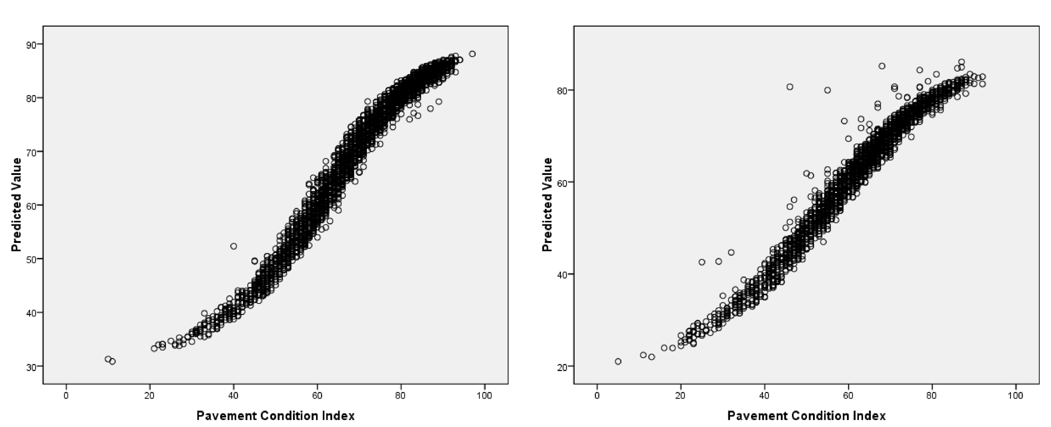
Error Estimation of Backpropagation Neural Network Models

Cases	Statistical significance	Arterial		Collector	
		Flexible	Rigid	Flexible	Rigid
Training	Sum of Squares Error	0.13	0.083	0.516	0.389
	Relative Error	0.051	0.105	0.033	0.036
Testing	Sum of Squares Error	0.135	0.472	1.024	0.741
	Relative Error	0.094	0.225	0.033	0.040
Validation	Relative Error	0.09	0.716	0.037	0.037

Predicted-by-observed scatterplot - Pavement Condition Index (PCI)

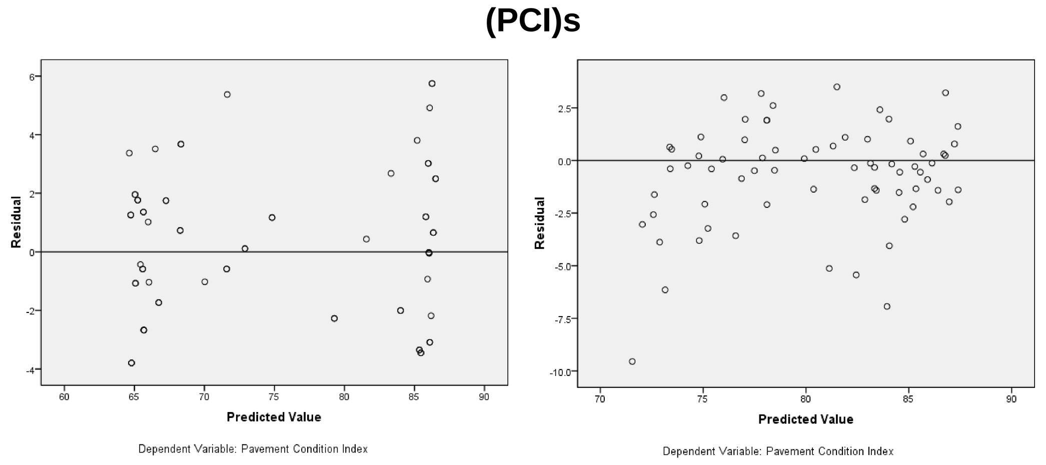


Arterial flexible pavement **Arterial rigid pavement**

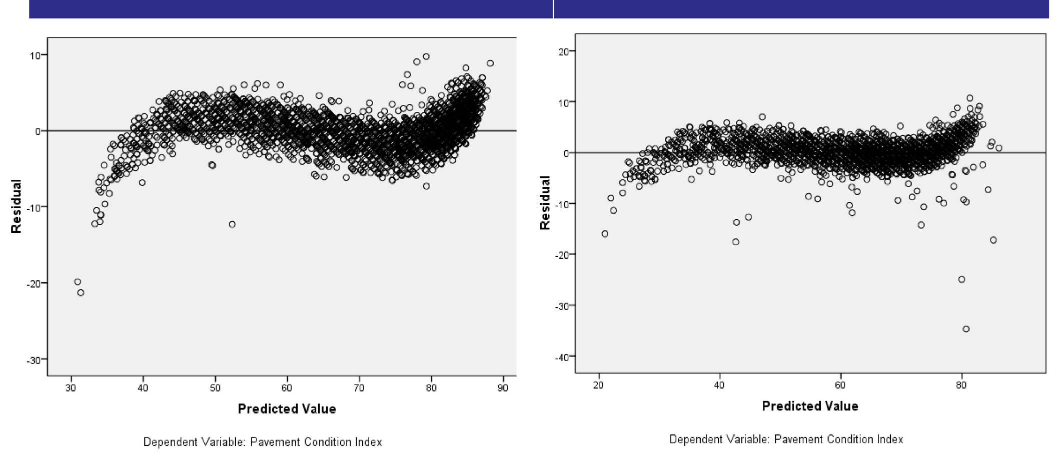


Collector flexible pavement **Collector rigid pavement**

Predicted-by-observed scatterplot - Pavement Condition Index (PCI)s



Arterial flexible pavement **Arterial rigid pavement**



Collector flexible pavement **Collector rigid pavement**

Results

Parameter estimation of the independent variables of PCI for Flexible pavements

Predictor		Predicted PCI for Arterial Roads						Predicted PCI for Collector Roads					
		Hidden Layer 1			Hidden Layer 2		Output Layer	Hidden Layer 1			Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI	H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI
Input Layer	(Bias)	-.647	-.541	-.523				-.460	.052	.115			
	∆PCI	3.877	1.576	-1.031				1.025	-.889	.838			
	Log_{10}(AADT)	-.086	-.249	.069				-.423	.253	-.265			
	Log_{10}(ESALs)	-.077	-.325	.005				-.176	.209	-.201			
	Pavement's Age (N)	-2.765	-1.207	.415				-.092	-.021	-.017			
	Structural Number (SN)	.020	.052	.622				.111	.368	.946			
Hidden Layer 1	(Bias)				.429	.646					.062	-.179	
	H(1:1)				-3.553	-2.520					1.367	-.676	
	H(1:2)				-1.720	-1.303					1.043	-.879	
	H(1:3)				-.712	-.017					-2.341	1.579	
Hidden Layer 2	(Bias)						-2.102						.222
	H(2:1)						4.151						4.063
	H(2:2)						4.034						-2.363

Parameter estimation of the independent variables of PCI for Rigid pavements

Predictor		Predicted PCI for Arterial Roads						Predicted PCI for Collector Roads					
		Hidden Layer 1			Hidden Layer 2		Output Layer	Hidden Layer 1			Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI	H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI
Input Layer	(Bias)	-.463	-.393	.115				-.045	-.379	-.041			
	∆PCI	-.340	1.288	.971				-.496	.511	.522			
	Log_{10}(AADT)	.661	-.059	-.097				.058	-.046	-.241			
	Log_{10}(ESALs)	.348	-.121	-.059				.296	-.060	-.546			
	Pavement's Age (N)	-.286	-1.850	-1.268				-.431	-.266	-.323			
	Slab Thickness (mm)	.440	.282	.745				.327	.157	.230			
Hidden Layer 1	(Bias)				.477	-.070					.284	.151	
	H(1:1)				.710	.685					1.686	2.079	
	H(1:2)				-.930	1.442					-1.685	-1.880	
	H(1:3)				1.380	-.565					-1.346	-1.210	
Hidden Layer 2	(Bias)						3.153						-2.462
	H(2:1)						2.987						3.292
	H(2:2)						-8.442						3.621

Importance of input variables to estimate PCI values in BPN networks

Input variables	Arterial		Collector	
	Flexible	Rigid	Flexible	Rigid
∆PCI	.364	.331	.330	.329
Log_{10}(AADT)	.138	.230	.226	.201
Log_{10}(ESALs)	.120	.194	.221	.248
Pavement's Age (N)	.363	.162	.123	.211
Structural Number (SN)	.015		.100	
Slab Thickness (mm), T		.083		.012

Conclusion

- This study applies BPN method with Generalized Delta Rule (GDR) learning algorithm for offsetting the statistical error of pavement performance modeling.
- ∆PCI significantly influence PCI values of flexible arterial, rigid arterial, flexible collector and rigid collector roads by 36.3%, 33.1%, 33% and 32.9% respectively.
- AADT and ESALs have considerable importance to estimate PCI values
- Pavement's age does not significantly influence PCI except for flexible arterial roads
- Structural characteristics of pavement do not have significant influence PCI values
- Complete historic record will enable to estimate more accurate pavement performance model by applying BPN network

REFERENCES

Attoh-Okine NO (1999) Analysis of Learning Rate and Momentum Term in Backpropagation Neural network Algorithm Trained to Predict Pavement Performance. Advances in Engineering Software 30:291-302.

Li, N., Haas, R., and Xie, W.-C. (1997). "Investigation of Relationship between Deterministic and Probabilistic Prediction Models in Pavement Management." Transportation Research Record: Journal of the Transportation Research Board, 1592, 70-79.