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Prediction of Road Condition and Smoothness for Flexible and Rigid Pavements in Louisiana Using Neural Networks

INTRODUCTION

DOTD currently employs a set of pavement condition deterioration curves, or prediction models (so-called family curves), in its network-level pavement preventive and rehabilitation treatments selection and budget planning through an infrastructure asset management software. These performance prediction models are typically developed using curve-fitting regression from existing pavement condition data collected in DOTD's PMS database by non-linear mathematical functions between each of selected pavement distress indices (e.g., roughness, rutting, alligator cracking, random cracking and patching indices) and pavement age. It is well known that the deterioration of a roadway's pavement surface conditions could be also impacted by different traffic loading, pavement structure, and climate factors, not just pavement service years. While the predicted pavement deterioration and conditions are core inputs for different pavement treatment selections, their accuracy directly influences the distribution of available resources. Therefore, there is a need to improve the network-level pavement condition prediction by incorporating other influential factors (e.g. structural, traffic, and climatic factors) into pavement condition prediction models using software computing techniques, such as artificial neural networks (ANN) and genetic algorithms.

OBJECTIVE

The objective of this research was to develop both short- and long- term pavement performance and deterioration models that can be used to estimate future pavement conditions and smoothness using ANN modeling. Specifically, the short-term models were for the prediction of 2- and 4-year future pavement surface cracking percentages for the current Louisiana interstate and national highway system (NHS) pavement network. The long-term models were developed as alternatives to DOTD's family curve models used in asphalt pavement maintenance and rehabilitation treatment selection.

METHODOLOGY

Two comprehensive pavement condition datasets were strategically developed through retrieving data files from various DOTD project data resources and the pavement management system (PMS) database. The short-term dataset was based on DOTD's Highway Performance Monitoring System (HPMS) data for predicting the federal cracking-percent for all interstate and national highway system (NHS) pavement segments in DOTD's pavement network, which contains approximately 40,000 0.1-mile asphalt and concrete pavement segments. Due to the lack of federal cracking condition data, only 4-year HPMS pavement condition data (2017-2020) were available for this study. The long-term modeling dataset included 255 asphalt overlay projects (thin or ultra-thin, medium and structural overlays) constructed after 2009, which were a total of 1348.5 lane-miles long and contain all highway functional classifications. For each selected project, all biennially-based PMS pavement condition data points (roughness, cracking and rutting) were collected. Specifically, all pavement performance prediction models were developed and analyzed using the MATLAB® computer programming platform. Each individual prediction model was specifically coded, trained, validated, and tested. To build short-term pavement cracking forecasting models, the selected NHS dataset was first divided into seventeen pavement groups according to pavement types (i.e., ASP, COM and JCP) and highway functional classifications (e.g., interstate, arterial, collector, urban, or rural). Each individual pavement group dataset was then rearranged for the modeling development based upon 0.1-mile pavement section data rows by linking 2017's cracking condition to 2019's, and 2018's to 2020's, with several section-related factors (e.g., pavement age, traffic and climate).

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Table 1 presents a summary of inputs and outputs for the developed short-term cracking performance models. In the analysis, the climate and weather data included annual average air temperature (AAT), annual average precipitation (AAP), annual average freezing index (AAFI), annual number of wet days (AAWD), average annual number of freeze/thaw cycles (AAFTC), which were obtained from a national weather database. In addition, both a feedforward ANN technique and a deep learning algorithm of Adaptive Neuro-Fuzzy Inference System (ANFIS) were studied and compared. Three commonly used training algorithms (Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient) and a k-fold cross validation approach were studied. Similarly, a set of incremental performance models of ANN were developed using PMS pavement condition data of selected overlay projects to predict network-level long-term pavement performance for IRI, rutting, percent cracking and five distress indices (ALCR, RNDM, PTH, RUT and RUFF). Table 2 presents the model name, inputs and outputs for the developed incremental performance models. Finally, a suite of ANN-based prediction models was developed for asphalt pavement distress family curves of various functional classes. These individual family curves were predicted based on weather factors (e.g., temperature, precipitation, and freeze-thaw cycles), traffic loading, pavement age, overlay thicknesses, and pavement functional classes.

Model name		Input	Output parameter
Pavement Type	Functional Class		
ASP	01	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAFI	%Cracking $_{(i)\ year}$
	02	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAFI	%Cracking $_{(i)\ year}$
	11	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAFTC	%Cracking $_{(i)\ year}$
	12	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAWD	%Cracking $_{(i)\ year}$
	14	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAP	%Cracking $_{(i)\ year}$
	16	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAFTC	%Cracking $_{(i)\ year}$
COM	01	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAP	%Cracking $_{(i)\ year}$
	02	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAFI	%Cracking $_{(i)\ year}$
	11	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAWD	%Cracking $_{(i)\ year}$
	12	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAP	%Cracking $_{(i)\ year}$
	14	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAWD	%Cracking $_{(i)\ year}$
	16	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAT	%Cracking $_{(i)\ year}$
JCP	01	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAP	%Cracking $_{(i)\ year}$
	02	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAFTC	%Cracking $_{(i)\ year}$
	11	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAT	%Cracking $_{(i)\ year}$
	12	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAT	%Cracking $_{(i)\ year}$
	14	Age $_{(i-2)\ year}$, %Cracking $_{(i-2)\ year}$, ADT$_{design}$, %Truck$_{design}$, AAWD	%Cracking $_{(i)\ year}$

Table 1. Input and Output Parameters for Short-Term Cracking Prediction Models

Model name	Input	Output
IRI	IRI$_{(i-4)}$, IRI$_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	IRI $_{(i)\ year}$
Rutting	RD$_{(i-4)}$, RD$_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	RD $_{(i)\ year}$
Percent of Alligator Cracking	CK$_{(i-4)}$, CK$_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	CK $_{(i)\ year}$
ALCR	ALCR$_{(i-4)}$, ALCR$_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	ALCR $_{(i)\ year}$
RNDM	RNDM$_{(i-4)}$, RNDM$_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	RNDM $_{(i)\ year}$
PTCH	PTCH $_{(i-4)}$, PTCH $_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	PTCH $_{(i)\ year}$
RUT	RUT$_{(i-4)}$, RUT$_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	RUT $_{(i)\ year}$
RUFF	RUFF $_{(i-4)}$, RUFF $_{(i-2)}$, age $_{(i)}$, accumulative truck, overlay_h, mill_h	RUFF $_{(i)\ year}$

Table 2. Input and Output Parameters for Incremental Performance Prediction Models

CONCLUSIONS

In this study, three types of pavement performance prediction models were developed, including 17 individual models for short-term, 8 for incremental long-term, and 5 for family curve generation. The following observations can be drawn:

- The developed ANN-based pavement performance models were capable of producing greater accuracy compared with statistical regression models for the network-level pavement performance prediction with higher R2 and lower RMSE values.
- It was found that both the feedforward ANN and ANFIS machine learning approaches were suitable for the short-term cracking percent prediction. The modeling results indicated that the ANN approach has the potential to be implemented in developing other short-term pavement condition prediction models.
- The developed incremental and family curve pavement performance models were found to be capable of making network-level long-term pavement performance predictions for IRI, rutting, percent cracking and five distress indices (ALCR, RNDM, PTCH, RUT, and RUFF) for all DOTD asphalt pavements.
- The developed family curve models are found more accurate than those generated in the current PMS system, which are only pavement aged based regression models.

RECOMMENDATIONS

- The short-term percent cracking models developed are recommended to be implemented directly into the FHWA-required pavement condition assessment analysis for DOTD's interstate and NHS pavements.
- The incremental long-term performance models developed are recommended for forecasting various pavement conditions when historical performance records are not sufficient for developing site-specific curves.
- The developed ANN pavement condition prediction models considering overlay pavement thickness, age, traffic, and climate factors as model inputs are recommended to be implemented as alternative family curve models currently used in DOTD's dTIMS with better accuracy and flexibility in pavement treatment selection.