Comparison of Feedforward and Recurrent Neural Networks for Predicting Pavement Roughness

CSHub Research Brief | Fengdi Guo | guofd@mit.edu

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Why do we need a recurrent neural network model?

Performance-based planning (PBP) is an important tool to mitigate the pervasive problem of inadequate budgets faced by transportation agencies. A key element for implementing PBP is efficient prediction of future pavement conditions. This depends on a robust deterioration prediction model.

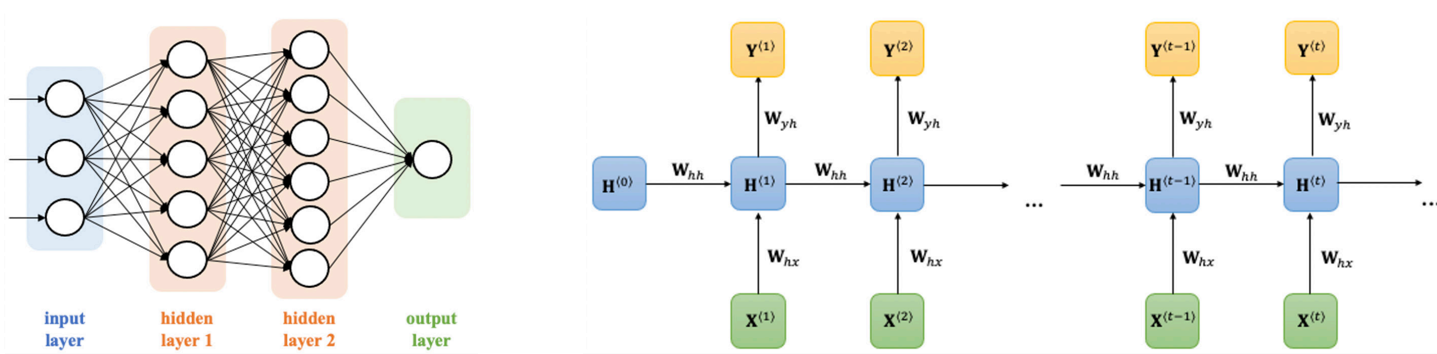
To efficiently describe the complicated nonlinear relationships embedded in pavement deterioration, the use of neural network models has expanded rapidly in pavement engineering. Most existing models are feedforward neural networks (FNN). These models are based on the Markovian assumption, which ignores the historical dependence during a pavement deterioration process. To bridge this research gap, a recurrent neural network (RNN) model is proposed to predict pavement roughness. This RNN model is compared to a FNN model to demonstrate the benefits of incorporating historical dependence.

Key Takeaways:

- The RNN model captures nonlinear relationships and historical dependence.
- The RNN model provides a better prediction performance compared to FNN in terms of pavement roughness.
- While the RNN model may take longer to train, it has significant potential for pavement performance prediction as more and better data are generated.

Model structure comparisons between FNN and RNN

Figure 1 (a) shows the structure of a feedforward neural network. It consists of an input layer, one or several hidden layers, and an output layer. Each layer has several



(a). (b).

Figure 1. Model structures for (a). feedforward neural network and (b). recurrent neural network.

neurons. The input layer incorporates all input data. Hidden layers are usually used to describe the nonlinear relationships. The output layer provides the final output. FNN is based on the Markovian assumption. At time t, it only requires the input $X^{\langle t \rangle}$ to predict the pavement condition $Y^{\langle t \rangle}$.

Figure 1 (b) shows the structure of a recurrent neural network (green color represents the input layer, blue color represents the hidden layer, and yellow color represents the output layer). Different from a FNN model, at time t, a RNN model requires the hidden layer $H^{\langle t \rangle}$ to generate the output $Y^{\langle t \rangle}$. This hidden layer $H^{\langle t \rangle}$ is obtained based on the input $X^{\langle t \rangle}$ and the hidden layer value at t-1, i.e. $H^{\langle t-1 \rangle}$. Similarly, $H^{\langle t-1 \rangle}$ is based on $X^{\langle t-1 \rangle}$ and $H^{\langle t-2 \rangle}$. Hence, $H^{\langle t \rangle}$ is calculated based on inputs $X^{\langle i \rangle}$ (i=1,2,…,t), and the historical information is stored in the hidden layer $H^{\langle t \rangle}$.

Data preparation and model training

The training of FNN and RNN models are based on the LTPP dataset. In addition to common parameters for pavement deterioration prediction, including pavement age, total thickness, traffic level, and environmental factors, several new input parameters that could reflect treatment history are also incorporated, including construction age, resurface age, surface thickness, sublayer thickness, and resurface number.

Figure 2 shows the heatmap for the correlations among initial parameters. Temperature (TEMP) and resurface number (RESNUM) are omitted due to their high correlations with other input variables. The final input features include construction age, resurface age,

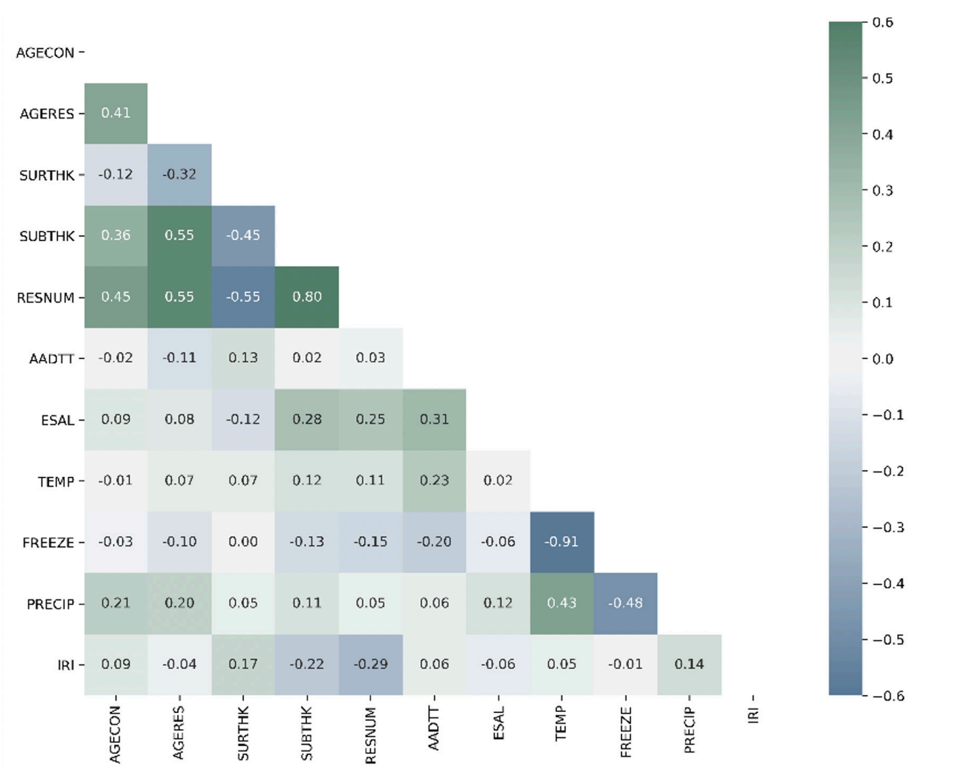


Figure 2. Correlations between input parameters.

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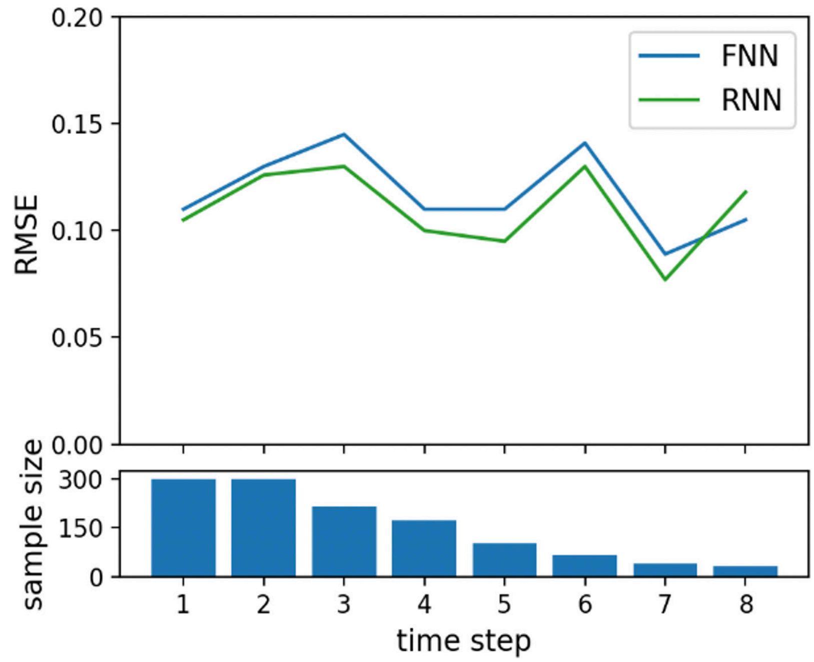

Figure 3. RMSE comparison at different time steps for FNN and RNN.

surface thickness, sublayer thickness, AADTT, ESAL, freeze index, and precipitation.

How successful was the model?

The RNN model has a slightly better prediction performance than the FNN model. The average root mean squared error (RMSE) for these two models based on 10-fold cross validation are 0.114 and 0.117, respectively. A two-sample t-test is applied to examine their statistically significant difference. With a 5% significance level, the corresponding p value is 0.006. This indicates a significant difference between these two models' performances.

The upper figure of Figure 3 shows the RMSE values for both FNN and RNN at different time steps. The lower figure shows the sample size at different time steps. Except for the last step, the RNN model performs better than the FNN model for all other time steps. The potential reason that RNN performs worse may be due to the small sample size at the last time step.

As for the training speed, FNN is faster. FNN takes 10s to train the model while the RNN takes 150s. This might suggest that the trade-off between the performance improvement and the training time may not justify the additional effort of the RNN model. However, since the training process is only conducted once, it is worth spending more time training the model to obtain better prediction performances for future applications. These results suggest that RNN may have significant potential for pavement performance prediction as more and better data are generated.

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