Vibration-Based Machine Learning Models for Condition Monitoring of Railroad Rolling Stock

Sergio Miguel Martinez[1] | Dr. Constantine Tarawneh[1] | Dr. Mohamadhossein Noruzoliaee[2]

[1]Department of Mechanical Engineering, [2]Department of Civil Engineering — The University of Texas Rio Grande Valley

INTRODUCTION

The University Transportation Center for Railway Safety (UTCRS) has been researching and developing new technologies for over a decade in an effort to prevent train derailments. One of the leading preventive measures currently being researched are machine learning algorithms. These machine learning algorithms are capable of processing the extensive library of experimental data to eventually be able to accurately predict the vibration response of railroad rolling stock from the mileage and loading conditions. An eXtreme Gradient Boosting (XGBoost) and a Neural Network (NN) model were developed. XGBoost is capable of outputting relatively accurate predictions at an extremely fast pace whilst Neural Networks are able to output highly accurate predictions. These algorithms will work in tandem with the UTCRS developed / HUM produced onboard monitoring sensors for validation. The onboard monitoring sensor can be seen in **Figure 1**.

Figure 1: UTCRS Developed / HUM Onboard Monitoring Sensor

MODEL SPECIFICATIONS

Machine learning algorithms utilize hyperparameters, which effect the learning process. These were optimized through the use of a GridSearchCV, which is a command in the sklearn library that allows the testing of each combination of a defined set of hyperparameters. For this model, a 5-fold cross validation was used. The scoring system for the GridSearchCV was to maximize the coefficient of determination value (R^2) and the negative root mean square (RMSE) values. To reiterate, the GridSearchCV tests each possible combination of hyperparameters and outputs the combination that is the most accurate with the least amount of error. The other model being tested was a neural network that used the same dataset trained by the Levenberg-Marquardt algorithm. This neural network had six hidden layers with a descending number of nodes as shown in **Figure 2**. It should be noted that the performance of the neural network model was determined by checking the Mean Squared Error (MSE).

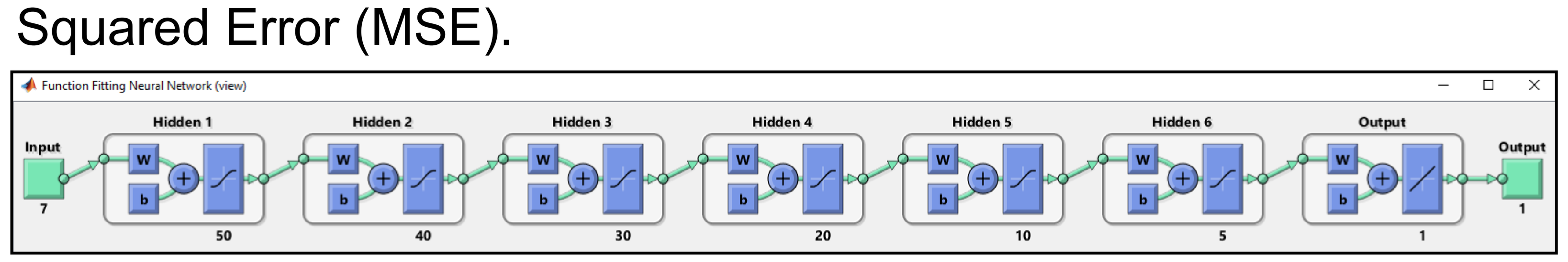

Figure 2: Neural Network Model

RESULTS

The outputs that the XGBoost model generated are listed in **Figures 3** and **4**. There are three graphs denoting the output of the training, validation, and testing dataset, respectively. The scoring parameters are the coefficient of determination, R^2, and the Root Mean Square Error, RMSE.

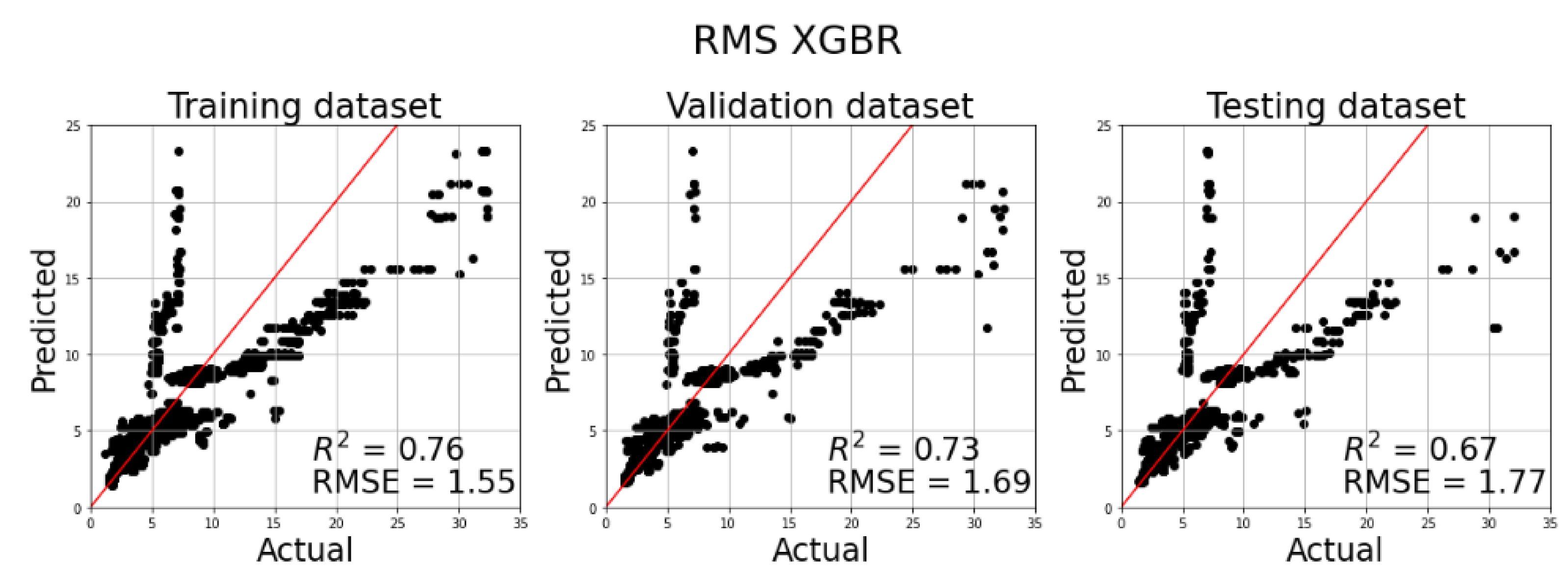

Figure 3: XGBoost for Regression RMS Results

The model uses a 60-20-20 split to obtain these results, meaning that 60% of the data is used to train, 20% is used to validate, and another 20% is used to test the predictions being made. The R^2 value ranges from 0 to 1 with the values closer to 1 being the most accurate. Thus, the results for the RMS model can be seen as being approximately 70% accurate with an error possibility of up to 177%. The maximum G model has a similar level of accuracy but a much larger range of error. This is likely due to the overabundance of maximum G data as it is essentially the raw data being utilized for the RMS calculations. The values for the hyperparameters used for the models are:

RMS		Max G	
Gamma	1.7	Gamma	0
Learning Rate	0.1375	Learning Rate	0.16
Max Depth	3	Max Depth	3
Number of Estimators	100	Number of Estimators	100
Regularization Lambda	1	Regularization Lambda	0.95

Table 1: XGBoost Hyperparameters

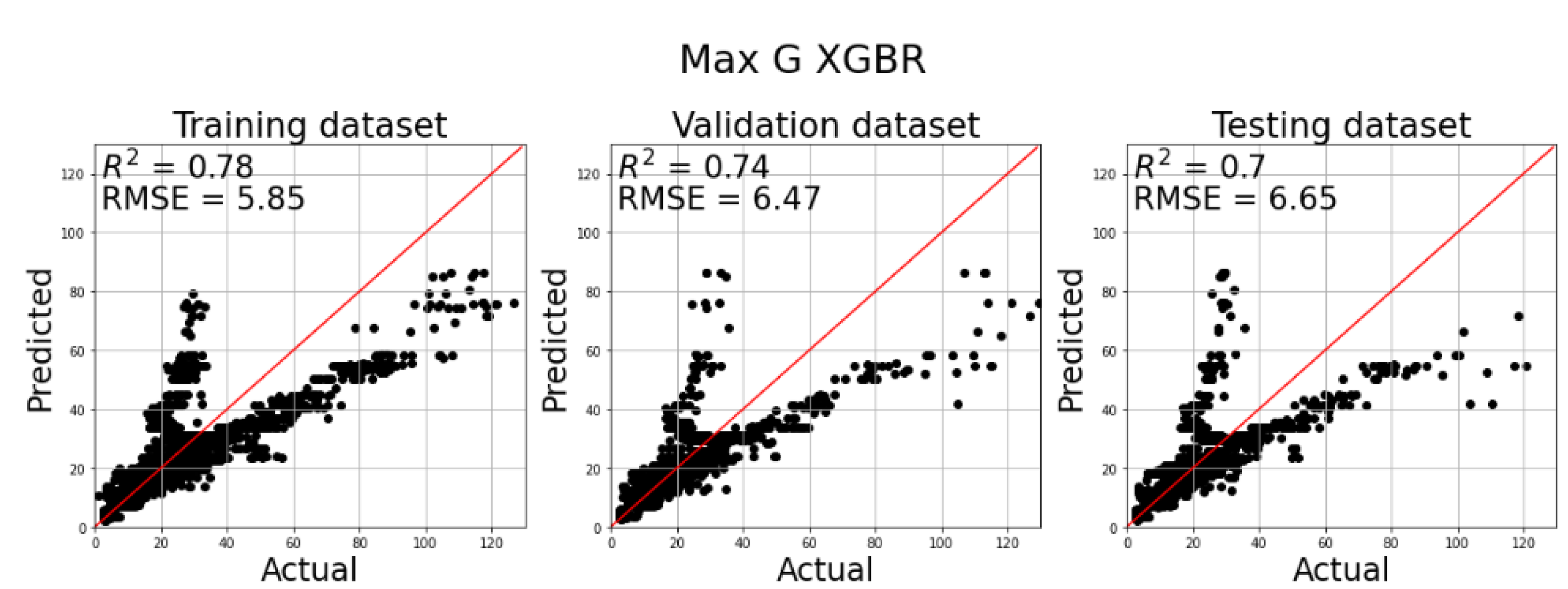

Figure 4: XGBoost for Regression Maximum G Results

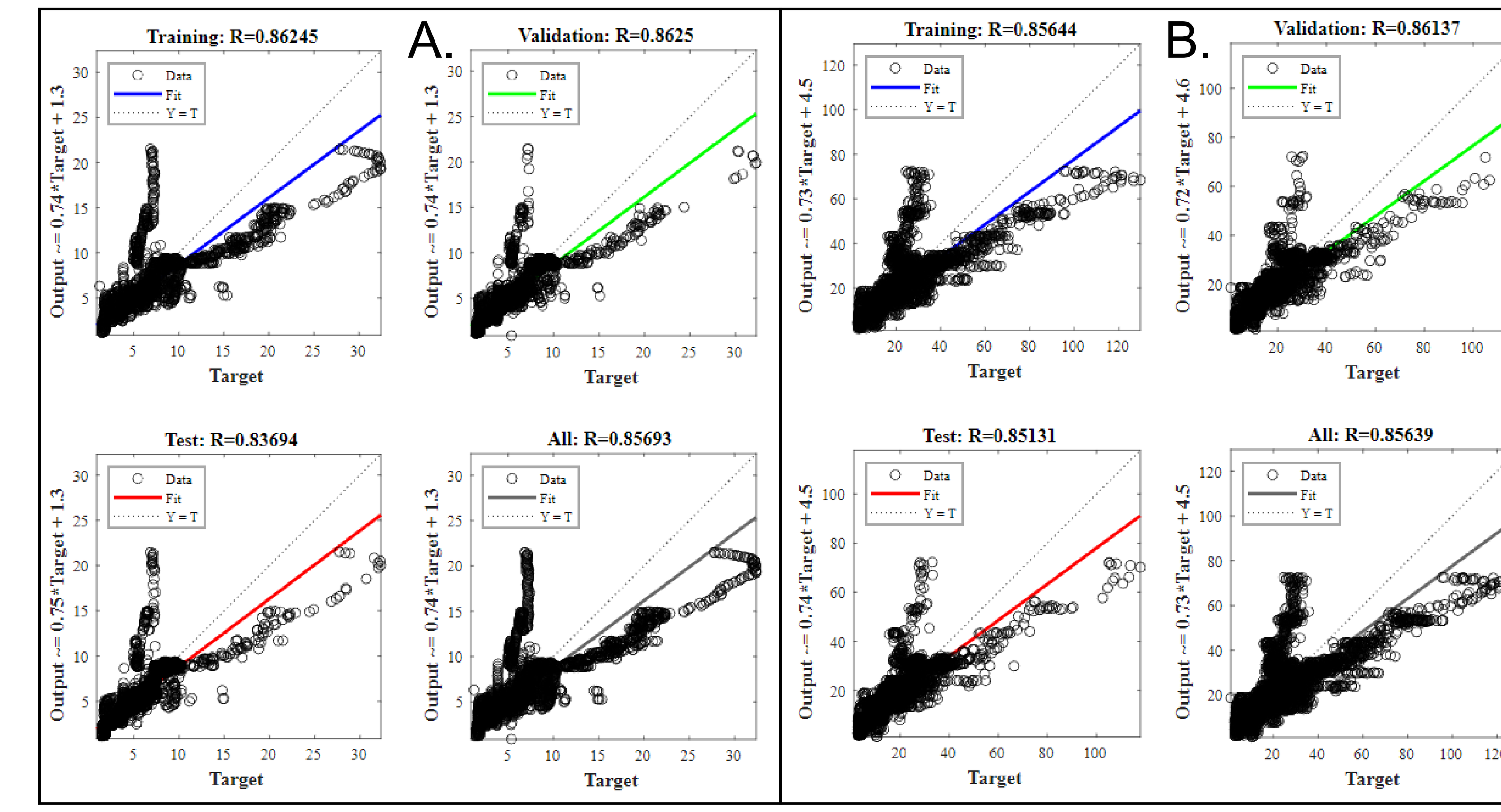

Figure 5: A. NN Regression RMS Results | B. NN Regression Max G Results

The Neural Network model predictions had an accuracy of 85.7% for the RMS model, and 85.6% for the maximum G model.

CONCLUSIONS

The XGBoost models were able to output results at a significantly faster pace than the Neural Network models but with lower accuracy. The Neural Network models were able to output 13.6% more accurate data when predicting the RMS and 11.6% more accurate data for the maximum G predictions. These results can likely be improved upon even further through more rigorous models, such as ones that utilize deep learning. These models output results that help predict one interval ahead at a time. To make these models more practical, time series forecasting will be applied and a deep Neural Network tailored for long term predictions will be developed.

ACKNOWLEDGEMENTS

The work presented here is sponsored by the CREST-MECIS center through NSF Award No. 2112650, and the Dwight David Eisenhower Transportation Fellowship Program (DDETFP) under US DOT Award No. 693JJ32345193.

REFERENCES

[1] Cantu, Lee R. Assessing the Effectiveness and Efficacy of Wireless Onboard Condition Monitoring Modules in Identifying Defects in Railroad Rolling Stock. Master's Thesis, The University of Texas Rio Grande Valley, December, 2021.

[2] Chen, Tianqi, et al. "Xgboost: extreme gradient boosting." R package version 0.4-2 1.4 (2015): 14.

[3] Buitinck, Lars, et al. "API design for machine learning software: experiences from the scikit-learn project." arXiv preprint arXiv:1309.0238 (2013).

[4] Moré, Jorge J. "The Levenberg-Marquardt algorithm: implementation and theory." Numerical analysis. Springer, Berlin, Heidelberg, 1978. 105-116.