

A Machine-Learning Based Tool to Predict Tire Noise Using Both Tire and Pavement  
Parameters.

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## **ABSTRACT**

Tire-Pavement Interaction Noise (TPIN) becomes the main noise source contributor for passenger vehicles traveling at speeds above 40 kph. Therefore, it represents one of the main contributors to noise environmental pollution in residential areas nearby highways. TPIN has been subject of exhaustive studies since the 1970s. Still, almost 50 years later, there is still not an accurate way to model it. This is a consequence of a large number of noise generation mechanisms involved in this phenomenon, and their high complexity nature. It is acknowledged that the main noise mechanisms involve tire vibration, and air pumping within the tire tread and pavement surface. Moreover, TPIN represents the only vehicle noise source strongly affected by an external factor such as pavement roughness. For the last decade, new machine learning algorithms to model TPIN have been implemented. However, their development relay on experimental data, and do not provide strong physical insight into the problem. This research studied the correct configuration of such tools. More specifically, Artificial Neural Network (ANN) configurations were studied. Their implementation was based on the problem requirements (acoustic sound pressure prediction). Moreover, a customized neuron configuration showed improvements on the ANN TPIN prediction capabilities. During the second stage of this thesis, tire noise test was undertaken for different tires at different pavements surfaces on the Virginia Tech SMART road. The experimental data was used to develop an approach to account for the pavement profile when predicting TPIN. Finally, the new ANN configuration, along with the approach to account for pavement roughness were complemented using previous work to obtain what is the first reasonable accurate and complete tool to predict tire noise. This tool uses as inputs: 1) tire parameters, 2) pavement parameters, and 3) vehicle speed. Tire noise narrowband spectra for a frequency range of 400-1600 Hz is obtained as a result.

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## **GENERAL AUDIENCE ABSTRACT**

Tire-Pavement Interaction Noise (TPIN) becomes the main noise source contributor for passenger vehicles traveling at speeds above 40 kph. Therefore, it represents one of the main contributors to noise environmental pollution in residential areas nearby highways. TPIN has been subject of exhaustive studies since the 1970s. Still, almost 50 years later, there is still not an accurate way to model it. This is a consequence of a large number of noise generation mechanisms involved in this phenomenon, and their high complexity nature. It is acknowledged that the main noise mechanisms involve tire vibration, and air pumping within the tire tread and pavement surface. Moreover, TPIN represents the only vehicle noise source strongly affected by an external factor such as pavement roughness. For the last decade, machine learning algorithms, based on the human brain structure, have been implemented to model TPIN. However, their development relay on experimental data, and do not provide strong physical insight into the problem. This research focused on the study of the correct configuration of such machine learning algorithms applied to the very specific task of TPIN prediction. Moreover, a customized configuration showed improvements on the TPIN prediction capabilities of these algorithms. During the second stage of this thesis, tire noise test was undertaken for different tires at different pavements surfaces on the Virginia Tech SMART road. The experimental data was used to develop an approach to account for the pavement roughness when predicting TPIN. Finally, the new machine learning algorithm configuration, along with the approach to account for pavement roughness were complemented using previous work to obtain what is the first reasonable accurate and complete computational tool to predict tire noise. This tool uses as inputs: 1) tire parameters, 2) pavement parameters, and 3) vehicle speed.

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# A Machine-Learning Based Tool to Predict Tire Noise Using Both Tire and Pavement Parameters.

Lucas Daniel Spies

## TABLE OF CONTENTS

|       |                                                            |    |
|-------|------------------------------------------------------------|----|
| 1     | Introduction.....                                          | 1  |
| 1.1   | Problem statement.....                                     | 1  |
| 1.2   | Background .....                                           | 2  |
| 1.2.1 | Tire Pavement Interaction Noise background.....            | 2  |
| 1.2.2 | Tire noise separation (Feng, 2017) .....                   | 6  |
| 1.2.3 | Artificial Neural Networks for TPIN prediction.....        | 8  |
| 1.3   | Thesis objectives .....                                    | 12 |
| 1.4   | Thesis organization .....                                  | 13 |
| 2     | Non-Negative Artificial Neural Network .....               | 14 |
| 2.1   | ANNs fundamentals .....                                    | 14 |
| 2.1.1 | Feed-forward ANN structure .....                           | 14 |
| 2.1.2 | ANN transfer functions.....                                | 17 |
| 2.1.3 | ANN training process .....                                 | 19 |
| 2.1.4 | Back-propagation algorithm .....                           | 22 |
| 2.2   | Non-negative ANN configuration.....                        | 26 |
| 2.2.1 | ANN configuration for curve fitting problems .....         | 27 |
| 2.2.2 | ANN configuration for positive outputs - constrained ..... | 28 |
| 2.2.3 | Unconstrained ANN configuration for positive outputs.....  | 29 |
| 2.2.4 | ANN configuration for noise prediction.....                | 32 |
| 3     | Pavement parameters related to TPIN .....                  | 33 |
| 3.1   | Pavement surface terminology.....                          | 33 |
| 3.2   | Experiments.....                                           | 35 |
| 3.2.1 | Equipment .....                                            | 35 |
| 3.2.2 | Roads tested .....                                         | 36 |
| 3.2.3 | Tires tested.....                                          | 40 |
| 3.3   | Experimental results.....                                  | 43 |
| 3.3.1 | Pavement data .....                                        | 43 |
| 3.3.2 | Tire noise data.....                                       | 50 |
| 3.4   | Pavement profile and tire noise relationship .....         | 52 |

|       |                                                                                                |     |
|-------|------------------------------------------------------------------------------------------------|-----|
| 3.4.1 | TPN independency from pavement profile.....                                                    | 52  |
| 3.4.2 | NTPN dependency from pavement profile .....                                                    | 54  |
| 3.4.3 | Conclusions.....                                                                               | 64  |
| 4     | Prediction of TPIN for different pavement surfaces.....                                        | 66  |
| 4.1   | NTPN prediction approach for non-porous pavements.....                                         | 66  |
| 4.1.1 | Approach description .....                                                                     | 66  |
| 4.1.2 | NTPN correction based on input pavement profile spectrum.....                                  | 69  |
| 4.1.3 | Weighting function (R-function) .....                                                          | 72  |
| 4.2   | Results and validation .....                                                                   | 83  |
| 5     | Full TPIN prediction model.....                                                                | 87  |
| 5.1   | Final model.....                                                                               | 88  |
| 5.2   | Model validation using only tire parameters.....                                               | 90  |
| 5.3   | Model validation using both tire and pavement parameters .....                                 | 97  |
| 5.4   | Model specifications and limitations.....                                                      | 103 |
| 6     | Conclusions and future work .....                                                              | 104 |
| 7     | References.....                                                                                | 106 |
| 8     | Appendix A: Non-negative ANN configuration for TPIN prediction using only tire parameters..... | 109 |
| 8.1   | Implemented transfer function configurations .....                                             | 109 |
| 8.2   | ANN for TPIN prediction code.....                                                              | 110 |
| 8.3   | Non-negative ANN configuration results .....                                                   | 112 |
| 8.3.1 | TPN results.....                                                                               | 112 |
| 8.3.2 | NTPN results.....                                                                              | 114 |
| 8.4   | Non-negative ANN configuration results .....                                                   | 115 |
| 9     | Appendix B: SMART road tire noise division information.....                                    | 117 |
| 9.1   | Experiments on the SMART road.....                                                             | 117 |
| 10    | Appendix C: U.S. Route 460 pavement distress.....                                              | 121 |
| 11    | Appendix D: Model validation results using only tire parameters .....                          | 123 |

# A Machine-Learning Based Tool to Predict Tire Noise Using Both Tire and Pavement Parameters.

Lucas Daniel Spies

## LIST OF FIGURES

|                                                                                                                                                                                  |    |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| Figure 1: Tire noise contribution by (R. Bernhard et al., 2005). .....                                                                                                           | 1  |
| Figure 2: OBSI system equipped with optical sensor to obtain the one-per-revolution signal to perform the tire noise separation. ....                                            | 7  |
| Figure 3: Tire noise signal superposed with optical sensor signal. ....                                                                                                          | 7  |
| Figure 4: Tire noise separation into TPN and NTPN components (Li et al., 2016). ....                                                                                             | 8  |
| Figure 5: TPIN prediction model by (Li, 2017). ....                                                                                                                              | 10 |
| Figure 6: Artificial Neural Network structure with one hidden layer. ....                                                                                                        | 15 |
| Figure 7: $i^{th}$ single neuron structure belonging to the ANN hidden layer. ....                                                                                               | 16 |
| Figure 8: Schematic of the ANN supervised learning process. ....                                                                                                                 | 19 |
| Figure 9: Example of overtraining of ANN. ....                                                                                                                                   | 20 |
| Figure 10: Validation step early stop criteria example (ANN training in MATLAB). ....                                                                                            | 21 |
| Figure 11: Error computation for the $n$ th neuron belonging to the output layer. ....                                                                                           | 23 |
| Figure 12: Pure linear transfer function implemented in the output layer. ....                                                                                                   | 28 |
| Figure 13: Symmetric sigmoid transfer function implemented in the output layer. ....                                                                                             | 29 |
| Figure 14: Hybrid transfer function implemented in the output layer. ....                                                                                                        | 31 |
| Figure 15: Pavement surface classifications and association with vehicle-pavement interaction characteristics. (ISO 13473-2:2002) .....                                          | 34 |
| Figure 16: OBSI system schematic and microphone denomination. ....                                                                                                               | 35 |
| Figure 17: Sideway-Force Coefficient Routine Investigation Machine (SCRIM) equipped with a scanning laser (sampling frequency 64 kHz) used to measure the pavement profile. .... | 36 |
| Figure 18: U.S. Route 460 road eastbound test section. ....                                                                                                                      | 37 |
| Figure 19: VTTI SMART road pavement sections. ....                                                                                                                               | 39 |
| Figure 20: 42 tires tested, 2 vehicles used, and OBSI system with optical sensor implemented for the U.S. Route 460 test. ....                                                   | 42 |
| Figure 21: Pictures of the OBSI setup and tread pattern of the tires tested on the SMART road. ....                                                                              | 43 |
| Figure 22: U.S. Route 460 road pavement profile. Complete length (top) and 50 cm example window (bottom). ....                                                                   | 44 |
| Figure 23: US460 road wavenumber (top), wavelength (middle) and frequency (bottom) pavement profile spectrums for a vehicle speed of 45 mph. ....                                | 47 |
| Figure 24: Pavement profile wavenumber spectrums of SMART road sections without transversal grooves. ....                                                                        | 48 |
| Figure 25: Pavement profile spectrums of SMART road sections with transversal grooves. ....                                                                                      | 49 |
| Figure 26: SMART road pavement profile spectrogram. ....                                                                                                                         | 49 |
| Figure 27: SMART road total tire noise spectrogram – Tire 24 – 60 mph. ....                                                                                                      | 50 |
| Figure 28: TPN and NTPN spectrums for different SMART road pavement sections. Noise data for tire 24 tested at 60 mph. Frequency resolution: 5 Hz. ....                          | 51 |

|                                                                                                                                                                                                                           |    |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| Figure 29: TPN spectrum comparison for the different pavements on the SMART road. Tire 24 – 32 psi – 60 mph. Continuous line: Asphalts, Dashed line: Concrete pavements. Frequency resolution: 20 Hz. ....                | 53 |
| Figure 30: SMART road TPN spectrogram – Tire 24 – 60 mph. ....                                                                                                                                                            | 53 |
| Figure 31: NTPN spectrum comparison for the different pavements on the SMART road. Tire 24 – 32 psi – 60 mph. Continuous line: Asphalts, Dashed line: Concrete pavements. Frequency resolution: 20 Hz. ....               | 54 |
| Figure 32: SMART road NTPN spectrogram – Tire 24 – 60 mph. Pavement with presence of transversal grooves highlighted. ....                                                                                                | 55 |
| Figure 33: SMART road section PCC-1c pavement profile example and frequency spectrum at 60 mph. Frequency resolution: 6.5 Hz (top). NTPN spectrum for tire 24. Frequency resolution: 5 Hz (bottom). ....                  | 57 |
| Figure 34: SMART road section PCC-1c pavement profile wavelength spectrum (top). SMART road section PCC-1c pavement profile 8 cm example window (bottom). ....                                                            | 58 |
| Figure 35: SMART road section PCC-1c NTPN spectrum for tire 24 at 45 mph. Frequency resolution: 5 Hz (bottom). ....                                                                                                       | 59 |
| Figure 36: SMART road sections F, I and PCC-1d pavement frequency spectrums at 55 mph. Frequency resolution: 6.5 Hz (top-left). NTPN spectrums for tire 20 (SRTT) at 55 mph. Frequency resolution: 5 Hz (bottom). ....    | 60 |
| Figure 37: SMART road sections F, I, PCC-1d and K pavement frequency spectrums at 55 mph. Frequency resolution: 6.5 Hz (top-left). NTPN spectrums for tire 20 (SRTT) at 55 mph. Frequency resolution: 5 Hz (bottom). .... | 62 |
| Figure 38: Porous pavement effect on tire noise (R. J. Bernhard et al., 2005). ....                                                                                                                                       | 63 |
| Figure 39: 50 cm window comparing a regular surface mix (SM) pavement profile with the open graded friction course (OGFC) pavement profile. ....                                                                          | 64 |
| Figure 40: SMART road pavements used for the development of the approach. ....                                                                                                                                            | 68 |
| Figure 41: Main objective of the proposed approach. ....                                                                                                                                                                  | 68 |
| Figure 42: NTPN pavement scaling process computation description. ....                                                                                                                                                    | 69 |
| Figure 43: NTPN spectrum - pavement profile spectrum transfer functions for Tire 24 for a vehicle speed of 60 mph for different non-porous pavements. Frequency resolution: 20 Hz. ....                                   | 73 |
| Figure 44: NTPN spectrum - pavement profile spectrum transfer functions for Tire 24 for a vehicle speed of 45 mph for different non-porous pavements. Frequency resolution: 20 Hz. ....                                   | 74 |
| Figure 45: R function computed for Tire 01 on pavement section E2 (dense graded mix) at vehicle speeds of 45, 50, 55, and 60 mph. Frequency resolution: 50 Hz. ....                                                       | 75 |
| Figure 46: R function computed for Tire 22 on pavement section J (dense graded mix) at vehicle speeds of 50, 55, and 60 mph. Frequency resolution: 50 Hz. ....                                                            | 76 |
| Figure 47: R function computed for Tire 20 on pavement section PCC-1b (concrete pavement surface) at vehicle speeds of 45, 50, and 55 mph. Frequency resolution: 50 Hz. ....                                              | 76 |
| Figure 48: Tires, vehicle speeds and pavement sections for which the R function was computed and studied. ....                                                                                                            | 77 |
| Figure 49: R function computed for Tire 24 on section G and Tire 01 on section J at different vehicle speeds. Frequency resolution: 50 Hz. ....                                                                           | 78 |

|                                                                                                                                                                                                                                                                                          |     |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| Figure 50: R function computed for Tire 24 on different pavement sections at different vehicle speeds. Frequency resolution: 50 Hz.....                                                                                                                                                  | 79  |
| Figure 51: R function computed for all tires (except Tire 22) on section E2 and section I for a vehicle speed of 45 mph. Frequency resolution: 50 Hz. ....                                                                                                                               | 80  |
| Figure 52: R function computed for different tires on different pavement sections at 45 mph. Frequency resolution: 50 Hz.....                                                                                                                                                            | 81  |
| Figure 53: Points for the averaged R function in linear scale, and 3-term Gaussian fitting curve.....                                                                                                                                                                                    | 83  |
| Figure 54: NTPN spectrums comparison between measured and predicted by current approach. Tire 01 – Section G – Vehicle speeds: 45-50-55-60 mph. Frequency resolution 5 Hz. ....                                                                                                          | 84  |
| Figure 55: NTPN spectrums comparison between measured and predicted by current approach. Tire 24 – Section PCC-1b – Vehicle speeds: 45-50-55-60 mph. Frequency resolution 5 Hz. ....                                                                                                     | 85  |
| Figure 56: NTPN OASPL comparison between measured and predicted by the proposed approach. ....                                                                                                                                                                                           | 86  |
| Figure 57: Full TPIN prediction model based on tire and pavement parameters. ....                                                                                                                                                                                                        | 88  |
| Figure 58: Main modules of the final AMOT model.....                                                                                                                                                                                                                                     | 89  |
| Figure 59: TPN order spectrum comparison in linear scale for a classic and the non-negative ANN configuration for (a) Tire 09 and (b) Tire 15. ....                                                                                                                                      | 91  |
| Figure 60: NTPN frequency spectrum comparison in linear scale for a classic and the non-negative ANN configuration for (a) Tire 09 and (b) Tire 15.....                                                                                                                                  | 91  |
| Figure 61: TTN, TPN and NTPN spectrums and OASPL comparison between measured and predicted data for Tire 09 at multiple vehicle speeds. Frequency resolution: 10 Hz. ....                                                                                                                | 92  |
| Figure 62: TTN, TPN and NTPN spectrums and OASPL comparison between measured and predicted data for Tire 23 at multiple vehicle speeds. Frequency resolution: 10 Hz. ....                                                                                                                | 93  |
| Figure 63: Comparison between measured and predicted overall A-weighted sound pressure level (OASPL) for the test tires. (a) Total tire noise, (b) Tread pattern noise, and (c) Non tread pattern noise.....                                                                             | 94  |
| Figure 64: Test tires tread pattern noise TPN OASPL ranking for 45, 50, 55 and 60 mph. ....                                                                                                                                                                                              | 95  |
| Figure 65: Test tires total tire noise TTN OASPL ranking for 45, 50, 55 and 60 mph. ...                                                                                                                                                                                                  | 96  |
| Figure 66: NTPN spectrums for Tire 22 on pavement section G for vehicle speeds of 50, 55 and 60 mph. Results shown for measured tire noise, predicted NPTN using only tire parameters, and predicted NTPN using both tire and pavement parameters. Frequency resolution: 10 Hz.....      | 98  |
| Figure 67: NTPN spectrums for Tire 22 on pavement section C for vehicle speeds of 50, 55 and 60 mph. Results shown for measured tire noise, predicted NPTN using only tire parameters, and predicted NTPN using both tire and pavement parameters. Frequency resolution: 10 Hz.....      | 99  |
| Figure 68: NTPN spectrums for Tire 22 on pavement section PCC-1b for vehicle speeds of 50, 55 and 60 mph. Results shown for measured tire noise, predicted NPTN using only tire parameters, and predicted NTPN using both tire and pavement parameters. Frequency resolution: 10 Hz..... | 100 |
| Figure 69: Comparison between measured and predicted NTPN overall A-weighted sound pressure level (OASPL) for the tires tested on the SMART road. (a) NTPN                                                                                                                               |     |

|                                                                                                                                                                                                                                                                   |     |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| predicted using only tire parameters and (b) NTPN predicted using both tire and pavement parameters. ....                                                                                                                                                         | 101 |
| Figure 70: Comparison between measured and predicted TTN overall A-weighted sound pressure level (OASPL) for the tires tested on the SMART road. (a) TTN predicted using only tire parameters and (b) TTN predicted using both tire and pavement parameters. .... | 102 |
| Figure 71: ANN output neurons transfer functions studied.....                                                                                                                                                                                                     | 109 |
| Figure 72: TPIN prediction model by (Li, 2017).....                                                                                                                                                                                                               | 110 |
| Figure 73: TPN acoustic sound pressure order spectrum for different ANN configurations. ....                                                                                                                                                                      | 113 |
| Figure 74: Configuration 1 outputs post-processing scheme for Tire 09. ....                                                                                                                                                                                       | 113 |
| Figure 75: Tread Pattern Noise OASPL comparison for test tires at all velocities. ....                                                                                                                                                                            | 114 |
| Figure 76: NTPN acoustic sound pressure frequency spectrum for different ANN configurations. ....                                                                                                                                                                 | 115 |
| Figure 77: Non-Tread Pattern Noise OASPL comparison for test tires at all velocities.....                                                                                                                                                                         | 115 |
| Figure 78: Pictures of tire noise test on the SMART road.....                                                                                                                                                                                                     | 117 |
| Figure 79: SMART road pavement sections.....                                                                                                                                                                                                                      | 118 |
| Figure 80: Different Pavement sections identification in the SMART road tire noise... ..                                                                                                                                                                          | 119 |
| Figure 81: (a) Total Noise spectrum, (b) Tread Pattern Noise spectrum, and (c) Non-Tread Pattern Noise spectrum. Frequency resolution: 5 Hz. ....                                                                                                                 | 121 |
| Figure 82: (left) Pictures of the US460, normal section and corrugated section, (right) Pavement profile wavelength spectrum. ....                                                                                                                                | 122 |
| Figure 83: Results of AMOT for Tire 09 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 124 |
| Figure 84: Results of AMOT for Tire 15 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 125 |
| Figure 85: Results of AMOT for Tire 18 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 126 |
| Figure 86: Results of AMOT for Tire 22 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 127 |
| Figure 87: Results of AMOT for Tire 23 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 128 |
| Figure 88: Results of AMOT for Tire 45 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 129 |
| Figure 89: Results of AMOT for Tire 49 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 130 |
| Figure 90: Results of AMOT for Tire 55 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).....                                                                                                     | 131 |

A Machine-Learning Based Tool to Predict Tire Noise Using Both Tire and Pavement Parameters.

Lucas Daniel Spies

**LIST OF TABLES**

|                                                                                                          |     |
|----------------------------------------------------------------------------------------------------------|-----|
| Table 1: TPIN generation mechanisms .....                                                                | 3   |
| Table 2: (Che et al., 2012) ANN Model .....                                                              | 9   |
| Table 3: (Li, 2017) ANN Model .....                                                                      | 11  |
| Table 4: Comparison between ANN models for TPIN prediction .....                                         | 11  |
| Table 5: ANN transfer functions.....                                                                     | 18  |
| Table 6: ANN configuration for noise prediction.....                                                     | 32  |
| Table 7: U.S. Route 460 road test information .....                                                      | 37  |
| Table 8: VTTI SMART road test information.....                                                           | 38  |
| Table 9: U.S. Route 460 road test tires information .....                                                | 41  |
| Table 10: SMART road test tires information .....                                                        | 42  |
| Table 11: U.S. Route 460 road spectrum parameters (spatial resolution $d_{samp} = 0.98\text{mm}$ ) ..... | 46  |
| Table 12: 3-term Gaussian curve fitting terms .....                                                      | 82  |
| Table 13: Main modules tasks description.....                                                            | 89  |
| Table 14: Tires used for both ANNs training. ....                                                        | 90  |
| Table 15: AMOT specifications.....                                                                       | 103 |
| Table 16: Investigated ANN transfer functions configurations for TPIN prediction. ....                   | 110 |
| Table 17: Inputs and outputs for each ANN <sub>TPN</sub> and ANN <sub>NTPN</sub> .....                   | 111 |
| Table 18: Tires used for both ANNs training. ....                                                        | 112 |
| Table 19: Test tires used to show the acoustic pressure spectrums results.....                           | 112 |

# 1 Introduction

## 1.1 Problem statement

During the last couple of decades, the transportation industry has experienced a remarkable growth. More specifically, passenger vehicles have become far more available, causing a dramatic increase in traffic noise. The noise levels produced by a single passing-by vehicle are not dangerous. However, this situation becomes critical in large cities, where areas close to highways are exposed to severe levels of road traffic noise (i.e., large amount of vehicles travelling at cruise speed). Vehicle exterior noise is divided into three main categories: 1) power-unit/drivetrain noise, 2) aerodynamic noise, and 3) tire-pavement interaction noise (TPIN) (Braun et al., 2013). The power-unit/drivetrain noise includes the engine noise, and both, the intake and exhaust systems noise. Both power-unit/drivetrain and aerodynamic noise have been improved with the latest automobile designs (i.e., quieter engines and exhausts, along with aerodynamically efficient vehicle designs). This is one of the reasons why TPIN is the main noise contributor to total exterior vehicle noise, mainly for driving speeds above 40 kph for passenger vehicles, and 70 kph for trucks as shown in Figure 1 (R. Bernhard et al., 2005).

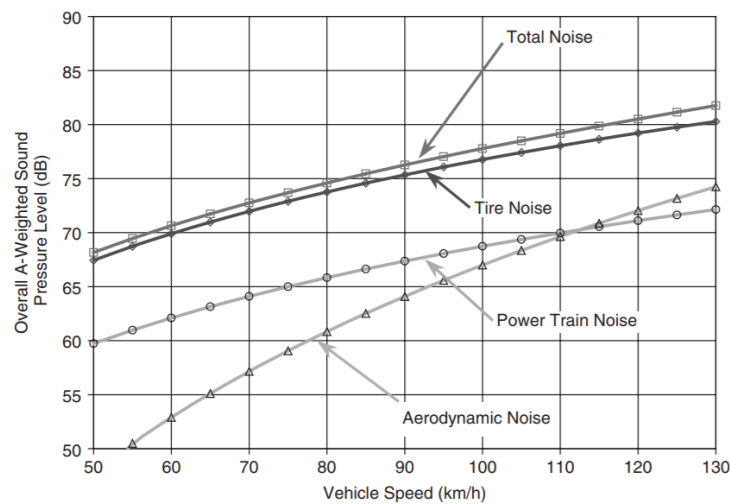


**Figure 1:** Tire noise contribution by (R. Bernhard et al., 2005).

The Federal Highway Administration (FHWA, 2010) presented five different noise mitigation options: 1) noise barriers, 2) vegetation screens, 3) traffic management, 4) building isolation and 5) buffer zones. Noise barriers are the most commonly used option. However, they are expensive and represent a poorly thought out and temporary solution to the problem. From the noise control point of view, the most effective strategy is to reduce the noise emitted by the source. This represents an important challenge for TPIN due to its complex nature. Even though the number of studies on TPIN have drastically increased during the last 50 years (T. Li et al., 2018), there is still not an accurate model to predict TPIN.

## **1.2 Background**

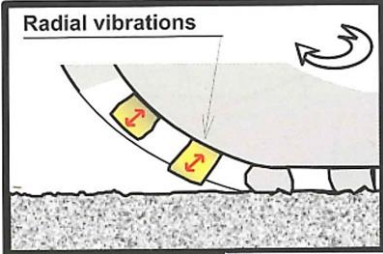
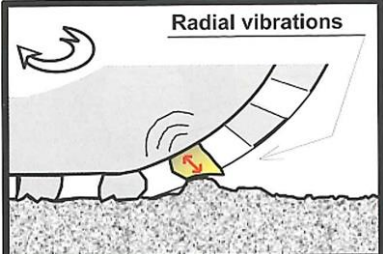
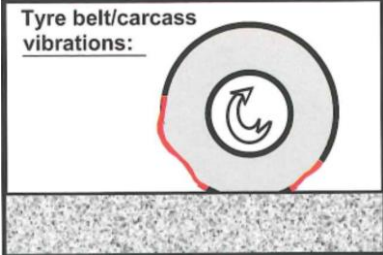
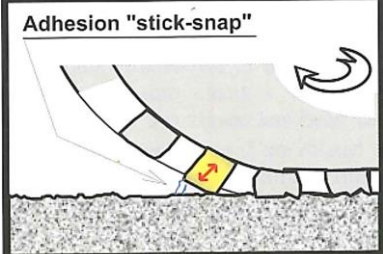
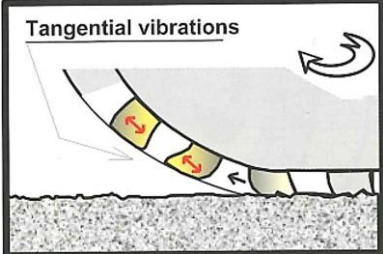
This section introduces different definitions and concepts that are extensively used in this thesis. Additionally, this work draws on previous studies. The author considers important to acknowledge the prior work of Jiangxiong Feng on tire noise separation (Feng, 2017) and Dr. Tan Li on tire noise predictions (Li, 2017). The highlights of their work are going to be briefly described.

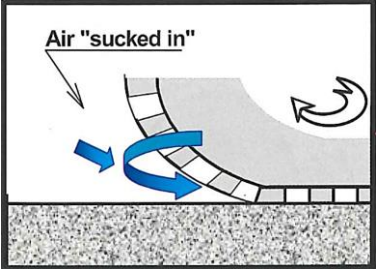
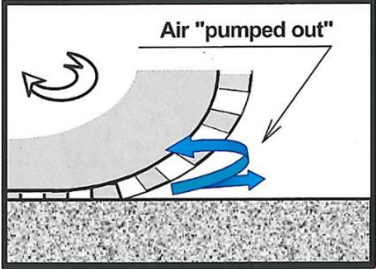
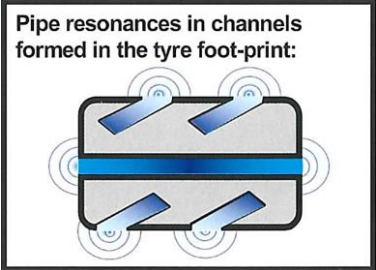
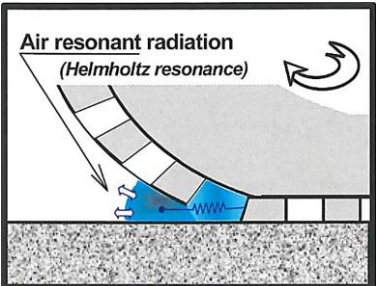
### *1.2.1 Tire Pavement Interaction Noise background*

Tire-Pavement Interaction Noise (TPIN) is defined as the noise generated from the interaction between a rolling tire and the pavement surface (Sandberg, 2001). It has been a major subject of study since the 1970s. As it was predicted, it has been the less improved noise source from passenger vehicles (Sandberg et al., 1980). The aerodynamic design and quieter engines have successfully diminished the noise radiated by other car components (Dechipre et al., 2010). Nowadays, TPIN is the major contributor of vehicle noise at highway speeds.

Although there are many theories about the noise generation mechanisms present in TPIN, the most accepted ones by the community are: 1) tire vibration due to the radial excitation at the tire contact patch and 2) pumping of the air between the tire and the road surface. They are also described as structure-borne and air-borne noise generation

mechanisms, respectively. Table 1 briefly describes each one of the TPIN generation mechanisms (Sandberg et al., 2002). This also helps to understand the complexity of TPIN.

| Table 1: TPIN generation mechanisms                  |                                                                                                                                                                                                                                                                                                      |                                                                                       |
|------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| Generation mechanism                                 | Description                                                                                                                                                                                                                                                                                          | Illustration                                                                          |
| <b>Tire vibration mechanisms – radial deflection</b> | <b>1) Tread impact:</b> the tire radial deflection is caused by the impact of the tread pattern on the road. The radial excitation is strongly related to the tire tread pattern design.                                                                                                             |    |
|                                                      | <b>2) Texture impact:</b> the tire radial deflection is caused by the pavement surface texture intrusion on the tire contact patch. In this case, the excitation depends on the road surface profile.                                                                                                |    |
|                                                      | <b>3) Contact patch deformation:</b> The tire radial deflection is caused by the rolling of the tire. Here, the radial deformation occurs when the contact with the pavement starts (i.e., leading edge of the contact patch) and when the contact finishes (i.e., trailing edge).                   |  |
|                                                      | <b>4) Tread elements stick/snap:</b> The tire tread is radially excited due the sticking of its elements with the road surface. If we consider the three previous radial deflections, the tread pattern stick causes an opposite radial deflection (from the inside to the outside of the tire.)     |  |
| <b>Tire vibration – tangential deflection</b>        | <b>5) Tread elements stick/slip:</b> The tire tread is tangentially excited because of its elements sticking with the road surface, and the relative motion between the two parts. However, the evidence shows that most of the noise is generated by the tire radial deflection (items 1 through 4) |  |

|                             |                                                                                                                                                                                                                                     |                                                                                                                                                                         |
|-----------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Air displacement mechanisms | 6) <b>Tire aerodynamic noise:</b> Noise produced by the air displaced due to the rolling tire.                                                                                                                                      | No illustration                                                                                                                                                         |
|                             | 7) <b>Air pumping:</b> Noise produced by the air displaced in and out of the cavities formed between the tire tread pattern and the road surface. This noise generation mechanism is strongly related to the tire rotational speed. |   |
|                             | 8) <b>Pipe resonances (tire grooves):</b> Noise produced by the air displaced inside the tire grooves. They are considered to be pipes.                                                                                             |                                                                                     |
|                             | 9) <b>Helmholtz resonances:</b> Noise produced by the displacement of air into and out of connected air cavities in the tire tread pattern and the road surface. In addition, it is amplified by the resonances.                    |                                                                                    |

A large amount of TPIN models and approaches can be found in the literature (T. Li et al., 2018). These models have increased in complexity, providing improved physical insight and results. However, there is still no accurate global TPIN model involving both tire and pavement surface parameters at the same time. This is mainly attributed to the complex nature of TPIN. Most of the models concentrate in one or two noise generation

mechanisms. Some of them only use tire parameters, while others implement only pavement parameters. In the end, the validation process of a model becomes a complicated task. The main reason has to do with the difficulty of separating the contributions of each different noise source from the total tire noise. Three main categories of TPIN models are found in the literature: 1) analytical models, 2) statistical models, and 3) hybrid models.

Analytical models are mainly developed using the physical principles governing the phenomena. The tire structure has been simplified and modeled as a plate (Larsson et al., 2002), as a ring (Kung et al., 1986) and as a shell (Kim et al., 2004). Models simulating the tire structural response have improved. Nevertheless, they are accurate for low frequencies ( $< 500$  Hz). TPIN dominant frequency range is between 600 and 1200 Hz, making these structural models not suitable.

As an example, a Finite Element Method (FEM) model is used to simulate the tire structural response. Parameters such as detailed tire geometry, tire materials and boundary conditions are required for this approach. Later, a Boundary Element Method (BEM) code is implemented to compute the acoustic response, using the FEM structural response results as inputs (Brinkmeier et al., 2008). It can be inferred that the more accurate the computed structural response is, the more accurate the computed acoustic field will be (Guolin et al., 2011). However, it is clear that the result of this model is only the noise due to the tire vibration. It will not provide any result regarding the noise produced by the air displacement. This becomes a clear example of a model focused on one of the noise generation mechanisms which neglects the noise from other mechanisms. On the other hand, Computational Fluid Dynamics (CFD) models have been applied to simulate the air behavior inside the deformed tire tread grooves (Gagen, 2000) and between the tire tread pattern and road surface (Gautam et al., 2016). Later, the acoustic sound pressure field is computed using the fluid pressure obtained from the CFD model. In this case, the model is focusing on the air pumping generation mechanism, not taking into account the tire vibration mechanism.

Statistical models are also semi-empirical models. They are obtained from the correlation of measured tire noise with different tire or pavement parameters. These models have been historically used to predict pass-by traffic noise (FHWA, 1998). They are more accurate than analytical models, mainly because they are based on experimental data (i.e.,

measured TPIN). However, they are not capable of accounting for a large range of possible conditions. Another drawback is that preprocessed physical parameters, such as pavement texture spectrum or tread pattern spectrum, are used to correlate with tire noise. In order to make corrections, they have to be translated back to the physical parameter they were computed from. The statistical models found in the literature include classic regression and principal component analysis models among others.

Finally, hybrid models have provided a better approach to this problem. They combine physical principles with empirical models. Physical preprocessing is conducted, in order to obtain intermediate inputs to statistical models. This provides a compromise between the physical insight of analytical models and accuracy of statistical models. Two relevant works are relevant: The first combines Genetic Algorithms (GA) with Back Propagation (BP) Neural Network for tire noise prediction (Che et al., 2012). The second model implements two ANNs for TPIN prediction (Li, 2017). The latter takes advantage of the tire noise separation concept (Li et al., 2018), which is explained in the following subsection.

### *1.2.2 Tire noise separation (Feng, 2017)*

Feng's work used order domain synchronous averaging to separate two different noise components from Total Tire Noise (TTN). As it was shown in the previous subsection, TPIN has many complex noise generation mechanisms, and isolating one from the other has proven to be an extremely difficult task. Still, Feng was able to prove that one component was directly related to the tread pattern geometry and periodic with the tire rotation. He called it Tread Pattern Noise (TPN). The second component is known as Non-Tread Pattern Noise (NTPN). It was obtained by subtracting the TPN component from the total noise. Additionally, NTPN is considered to be independent of the tread pattern geometry, and related to other parameters such as rubber hardness and pavement surface features. Feng and co-researchers presented a novel setup that allows tire noise separation to be performed. It includes an On-Board Sound Intensity (OBSI) system (AASHTO, 2016) equipped with an optical sensor, as shown in Figure 2.

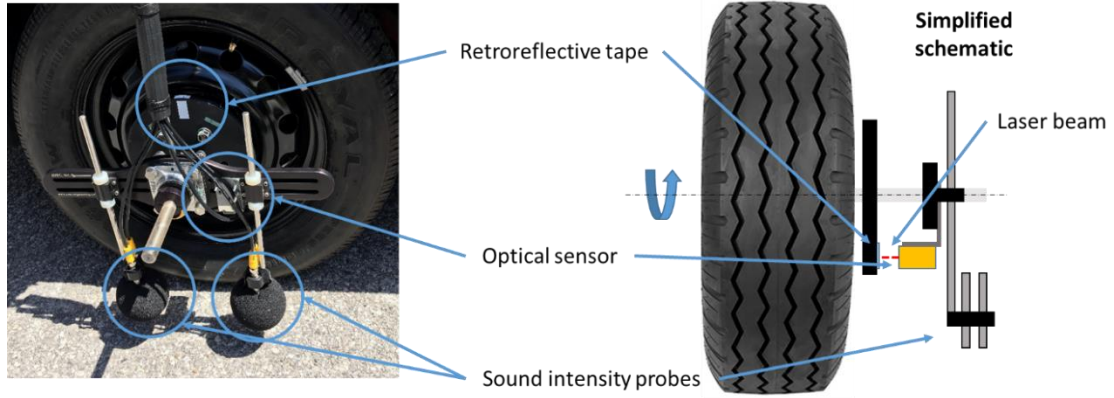


**Figure 2:** OBSI system equipped with optical sensor to obtain the one-per-revolution signal to perform the tire noise separation.

The main objective of the optical sensor is to obtain the one per revolution signal of the tire. When superposing both tire noise and optical sensor signal, the noise data can be divided into windows representing one tire revolution, as shown in Figure 3.

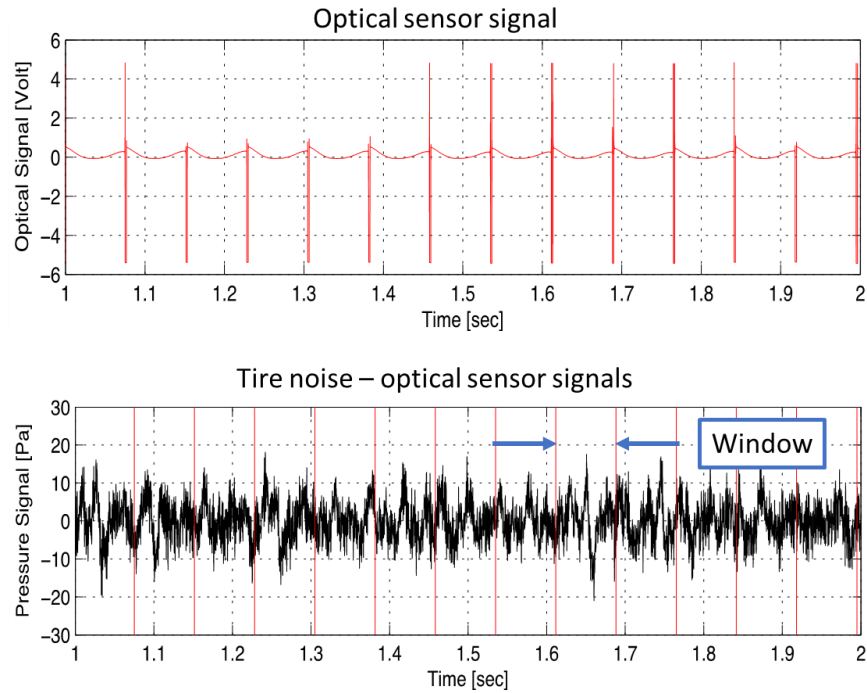


**Figure 3:** Tire noise signal superposed with optical sensor signal.

The signal inside each window is resampled to a fixed number of points. Then, the Fourier Transformation is performed to the data inside each window. The TPN spectrum is obtained by coherently averaging the Fourier Transformed data of each window. The

next step is to perform the Inverse Fourier Transform to obtain the TPN in time domain. This data is subtracted from the total tire noise, resulting in the NTPN component time history. Figure 4 shows a schematic of the tire noise separation procedure. Feng showed qualitatively that parameters such as the tread pattern coherent spectrum and air volume velocity spectrum are strongly related to the TPN component. Specifically, he indicated that the tread pattern design impacts the tire noise periodic components.

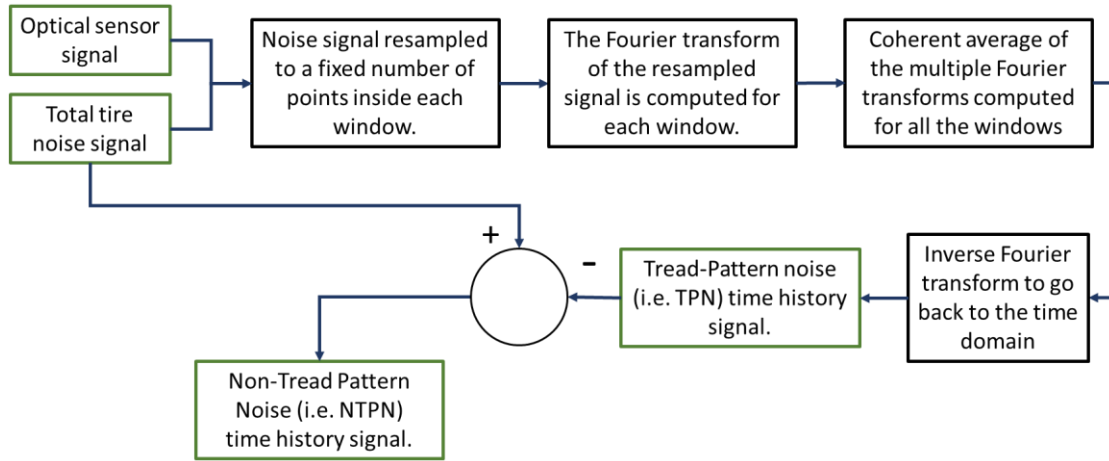


**Figure 4:** Tire noise separation into TPN and NTPN components (Li et al., 2016).

In this thesis, the concepts of Tread Pattern Noise and Non-Tread Pattern Noise are going to be extensively used.

### 1.2.3 Artificial Neural Networks for TPIN prediction

During the last decade, Machine Learning algorithms have been implemented to predict TPIN. Relevant work includes Che (2012), who successfully implemented a feed-forward ANN to predict TPIN. The ANN was complimented with Genetic Algorithms (GA) to optimize the initial weights and biases where the ANN started its training. The ANN also used the back propagation algorithm to update parameters during the training process. The model consisted of a single ANN, where the inputs were related to tire and vehicle operation parameters. The outputs of Che’s model were Sound Pressure Levels (SPL) in octave bands. The list of inputs and outputs are shown in Table 2.

For the ANN training process, Che used tire noise data collected using a rotating drum test. This data was divided into two subsets: 1) a training set consisting of 50 samples and 2) a test set consisting of 10 samples. In order to complete the training, the target error was set to  $1 \times 10^{-5}$ , and the maximum training iterations to 6000. The average error reported by Che for the test set was 1.4%. This error is computed as the average error between measured and predicted sound pressure levels for the 6 octave frequency bands.

| Table 2: (Che et al., 2012) ANN Model |                      |                                                                                                                                                                                                                                                                                                                                   |
|---------------------------------------|----------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                       | Parameter            | Description                                                                                                                                                                                                                                                                                                                       |
| <b>Inputs</b>                         | Tire size            | 1. Tire width<br>2. Tire aspect ratio<br>3. Tire radius                                                                                                                                                                                                                                                                           |
|                                       | Tread pattern        | 4. Area of single-pitch tread pattern block<br>5. Area of single pitch tread pattern groove<br>6. Number of tread blocks per pitch<br>7. Total number of pattern pitches<br>8. Arrangement rule of pitches<br>9. Displacement between the pattern strips<br>10. Symmetrical characteristics of tread patterns<br>11. Groove depth |
|                                       | Operation            | 12. Vehicle speed<br>13. Tire load<br>14. Inflation pressure                                                                                                                                                                                                                                                                      |
| <b>Outputs</b>                        | Sound pressure level | 1. SPL at the octave band of 125 Hz<br>2. SPL at the octave band of 250 Hz<br>3. SPL at the octave band of 500 Hz<br>4. SPL at the octave band of 1000 Hz<br>5. SPL at the octave band of 2000 Hz<br>6. SPL at the octave band of 4000 Hz                                                                                         |

The second relevant work was performed by Li (2017). Feng's tire noise separation concept introduced in subsection 1.2.2 allowed Li to create two separate ANNs. One is meant to predict TPN, which was denoted as ANN<sub>TPN</sub>. The second ANN predicts NTPN, and it is called ANN<sub>NTPN</sub>. Figure 5 shows a simplified scheme of the model structure proposed by Li.

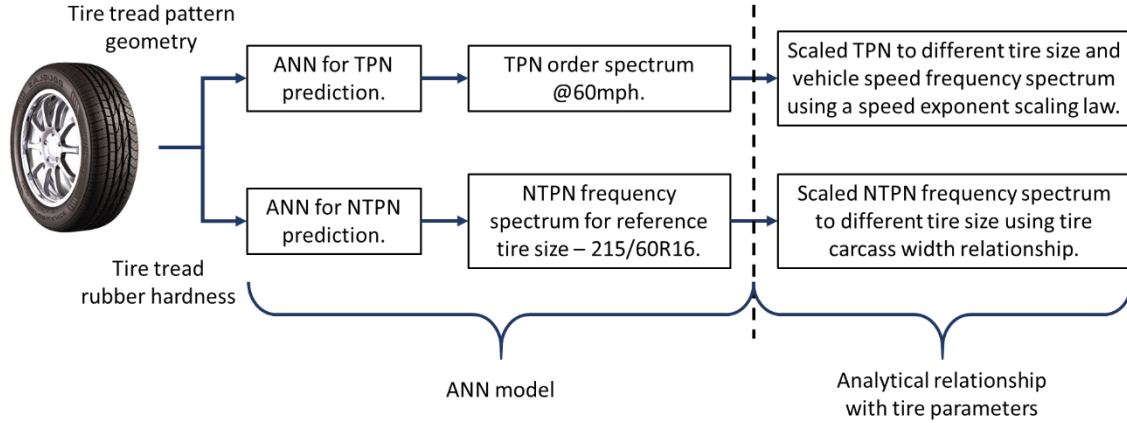


**Figure 5:** TPIN prediction model by (Li, 2017).

In his work, the influence of many different tire parameters on the two noise components was investigated. The main conclusions were:

1. In order to predict tread pattern noise, coherently averaged tread pattern spectra should be taken into account.
2. Another tread pattern geometry parameter strongly related to TPN is the air volume spectra.
3. Non-tread pattern noise is more closely related to the vehicle speed and the tread rubber hardness. If the tire noise data was collected on one pavement surface, the pavement is considered an invariant.

In order to train the ANNs, Li used tire noise data obtained using the OBSI system on an actual road test instead of a drum. Moreover, the tire noise separation technique was used to divide the tire noise into the TPN and NTPN components to train each ANN independently. The inputs and outputs are different for each ANN. Table 3 shows the information about Li's model.

| Table 3: (Li, 2017) ANN Model              |        |                                          |                                                                                                                                                                                                                                                        |
|--------------------------------------------|--------|------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| ANN                                        |        | Parameter                                | Description                                                                                                                                                                                                                                            |
| ANN for Tread Pattern Noise prediction     | Inputs | Tread pattern.                           | <ol style="list-style-type: none"> <li>1. Tread pattern profile spectrum: 6 coefficients for a two-term Gaussian curve approximation.</li> <li>2. Air volume velocity spectrum: 6 coefficients for a two-term Gaussian curve approximation.</li> </ol> |
|                                            | Output | Acoustic sound pressure ( $p_{rms}^2$ ). | <ol style="list-style-type: none"> <li>1. Root mean square acoustic sound pressure (<math>p_{rms}^2</math>) narrowband order spectra (order range 40-120). Prediction for a reference tire size and a vehicle speed of 60 mph.</li> </ol>              |
| ANN for Non-Tread Pattern Noise prediction | Inputs | Tire parameter.                          | <ol style="list-style-type: none"> <li>1. Rubber hardness.</li> </ol>                                                                                                                                                                                  |
|                                            |        | Operation.                               | <ol style="list-style-type: none"> <li>1. Tire rotational speed.</li> </ol>                                                                                                                                                                            |
|                                            | Output | Acoustic sound pressure ( $p_{rms}^2$ ). | <ol style="list-style-type: none"> <li>1. Root mean square acoustic sound pressure (<math>p_{rms}^2</math>) narrowband frequency spectra (frequency range: 400-1600 Hz, resolution: 10Hz). Prediction for a reference tire size (215/60R16)</li> </ol> |

In order to train the ANN, Li adopted the cross-validation method. This allows the ANN training to be stopped before it overfits the problem (i.e., before it loses the generalization capability).

The two works presented are the most relevant regarding TPIN modelling using machine learning algorithms. Table 4 shows the comparison between both hybrid models characteristics.

| Table 4: Comparison between ANN models for TPIN prediction |                                                                                                                                                                |                                                                                                                                                                                                                                                                                                                                    |
|------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Characteristics                                            | Che Model (Che et al., 2012)                                                                                                                                   | Li Model (Li, 2017)                                                                                                                                                                                                                                                                                                                |
| ANN model.                                                 | 1 ANN (1 hidden layer).                                                                                                                                        | 2 ANNs (1 hidden layer) <ol style="list-style-type: none"> <li>1. ANN<sub>TPN</sub>: Predicts TPN.</li> <li>2. ANN<sub>NTPN</sub>: Predicts NTPN</li> </ol>                                                                                                                                                                        |
| Inputs                                                     | Tire parameters: tire size, tread pattern blocks and grooves.                                                                                                  | <ol style="list-style-type: none"> <li>1. ANN<sub>TPN</sub>: tread pattern spectrum and air volume spectrum.</li> <li>2. ANN<sub>NTPN</sub>: Rubber hardness, tire rotational speed.</li> </ol>                                                                                                                                    |
| Outputs                                                    | Sound pressure levels at octave bands (125 Hz, 250 Hz, 500 Hz, 1kHz, 2 kHz and 4 kHz)                                                                          | <ol style="list-style-type: none"> <li>1. ANN<sub>TPN</sub>: Acoustic sound pressure (<math>p_{rms}^2</math>) in order spectrum (orders range: 40 - 120)</li> <li>2. ANN<sub>NTPN</sub>: Acoustic sound pressure (<math>p_{rms}^2</math>) in narrowband frequency spectrum (400-1600 Hz with 10Hz frequency resolution)</li> </ol> |
| ANN neurons configuration                                  | <ol style="list-style-type: none"> <li>1. Hidden layer: logistic sigmoid transfer function</li> <li>2. Output layer: pure linear transfer function.</li> </ol> | <ol style="list-style-type: none"> <li>1. Hidden layer: logistic sigmoid transfer function</li> <li>2. Output layer: pure linear transfer function.</li> </ol>                                                                                                                                                                     |

Using Table 4 as reference to compare both models, Li's work better captured the details of the tread pattern geometry when providing them as inputs to the ANN. In addition, the tire noise separation concept allowed Li to divide the tire parameters into the relevant ones for each tire noise component. Historically, tire noise has been related to Overall A-Weighted Sound Pressure Levels (OASPL). This does not provide any insight on the frequencies where the noise is dominant. The work by Li outperforms the one presented by Che, because the ANN model is capable of predicting noise in narrowband rather than octave bands. In Li's work the ANNs are not created to predict the final tire noise. They are used to model tire noise at a fixed speed (TPN case) and a fixed tire size (NTPN case). Later, the noise is scaled to other speeds and tire sizes using different parameter relationships (i.e., analytic relationships). Somehow, this alleviates the ANN work to fit an extremely complex problem such as TPIN and improves its results. As a conclusion, part of the prediction is performed by the ANNs, while other steps use the analytical relationship between the noise and tire parameters.

None of the models includes pavement parameters as inputs to the ANN. This is mainly because it would increase the complexity of the phenomena to be modeled. Both models are only able to predict tire noise for a specific pavement surface (i.e., pavement where the experimental data used to train the ANN was acquired). Another important missing point in both works is the ANN configuration. An ANN can be a powerful computational tool, as long as it is correctly configured for the desired purpose. If that is not the case, the final results will not be accurate. All the previous analysis provides plenty of information to define the goals of this thesis.

### **1.3 Thesis objectives**

The main goal of this thesis is to develop a machine learning-based model for TPIN prediction. The model will use both tire and pavement parameters to make the noise predictions. The main objectives are:

1. Define the correct configuration of an ANN meant to predict noise. For this specific thesis, TPIN prediction is of interest. This will be done by studying the

fundamental theory of Artificial Neural Networks (ANNs), and applying it to tire noise.

2. Investigate the effects of different pavements surfaces on TPIN. Moreover, tire noise data along with pavement surface profile data will be used to test the hypothesis that: *Tread Pattern Noise is independent of the pavement surface profile, while Non-Tread Pattern Noise is dependent of it.*
3. Develop a methodology to account for the pavement surface profile characteristics when predicting TPIN.
4. Apply the knowledge from previous tasks, in conjunction with the model created by Li, to develop a comprehensive tool to predict TPIN using both tire and pavement parameters.

## **1.4 Thesis organization**

The thesis has six chapters. The first chapter presents the main problem, providing a brief background on TPIN and previous relevant work. In addition, the main goals of this thesis and the document organization are explained. Chapter 2 introduces ANN's fundamental theory. Additionally, a configuration to predict only positive values is investigated and developed. Chapter 3 briefly introduces pavement parameters related to TPIN. The analysis of experimental tire noise data collected for different pavements is presented. Physical insight of TPIN's relationship with different pavement surfaces is shown. Chapter 4 introduces the approach to account for the pavement profile when predicting TPIN. This is done for the specific case of non-porous pavements without transversal grooves. Chapter 5 presents the final results of the ANN based model developed to predict TPIN using both tire and pavement parameters. Chapter 6 provides the thesis conclusions and future work.

## 2 Non-Negative Artificial Neural Network

In this chapter, the Non-Negative ANN configuration will be presented. First, the ANNs fundamentals will be introduced. Then, their application for noise prediction will be investigated. Finally, the specific configuration to obtain only positive results will be presented.

### 2.1 ANNs fundamentals

Simon Haykin (1994) defines the brain as a “highly complex, nonlinear and parallel computer.” Artificial neural networks are nonlinear mapping systems whose structure is based on the human brain (Reed et al., 1999). An elemental unit capable of performing basic computation processes is not expected to be useful for solving large and complex problems. However, a model with a large number of these basic entities (i.e., neurons) interconnected with each other is able to deal with complex nonlinear problems in an accurate way. ANNs have been widely applied in computational problems such as pattern recognition, image processing, intelligent control, prediction and so forth (Tang et al., 2007).

This section explains the structure of a *feed-forward multilayer* ANN. Then, the working principle of this specific ANN model will be presented. In addition, the computation that takes place in the basic constitutive element (i.e., neuron) is explained. Finally, the ANN training process along with the back-propagation algorithm will be described.

#### 2.1.1 *Feed-forward ANN structure*

The most common structure used for ANNs is shown in Figure 6. It is known as *feed-forward multilayer* structure. Feed-forward describes how the information travels through the model (i.e., always from the inputs side to the outputs side).

A single layer network consists only of an input and an output layer. A multilayer ANN implements hidden layers located between the input and output layers, as seen in Figure 6.

The amount of hidden layers depends on the complexity of the problem to be handled by the ANN. In addition, if any neuron present in any layer is connected to all the neurons present in the previous layer, the network is called a fully connected neural network (Haykin, 1994). Figure 6 shows the presence of an input layer, one hidden layer and an output layer.

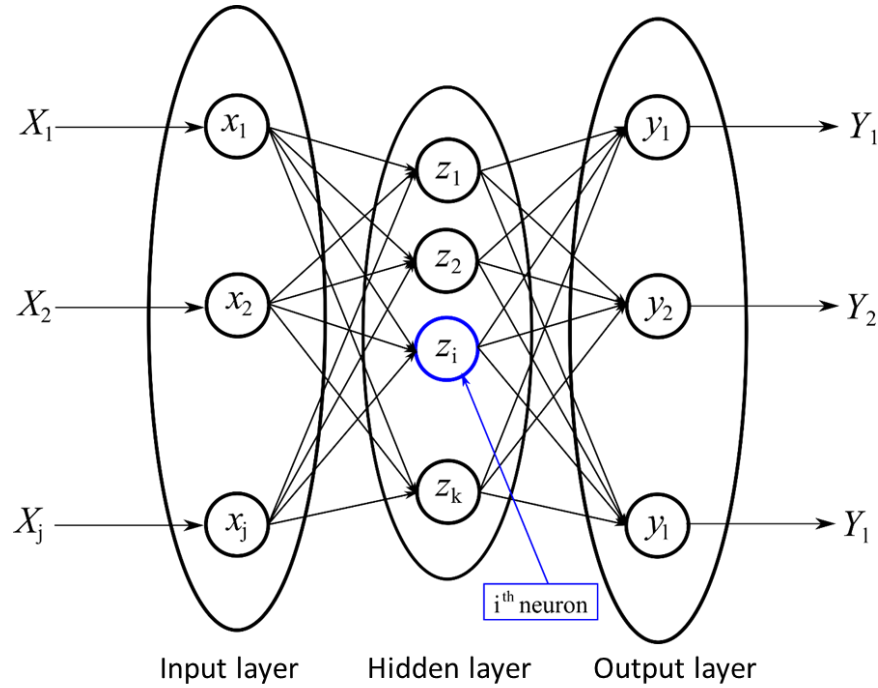


**Figure 6:** Artificial Neural Network structure with one hidden layer.

Each layer of the ANN is constituted by a basic element: the neuron. Figure 7 shows the internal structure of the neuron highlighted in Figure 6. It is the neuron configuration for each layer which dictates how the ANN will behave.

The ANN structure shown in Figure 6 has “j” neurons in the input layer (i.e.,  $x_1, x_2, x_3, \dots, x_j$ ). Strictly speaking, the input layer is different from the hidden and output layers. The input values (i.e.,  $X_1, X_2, X_3, \dots, X_j$ ) and the target values (i.e.,  $Y_1, Y_2, Y_3, \dots, Y_l$ ) used during the training of the ANN are subject to a normalization process. Equation 2.1 shows the computation process that takes place in the  $n^{th}$  neuron ( $x_n$ ) belonging to the input layer.

$$x_n = (b - a) \frac{X_n - \min(X)}{\max(X) - \min(X)} + a \quad (2.1)$$

In equation 2.1,  $X_n$  represents the input value of the  $n^{th}$  neuron and  $a$  and  $b$  are the lower and upper limit for the normalized range, respectively. Therefore, the inputs to the ANN are values within a normalized range of  $[a; b]$ . For the current explanation, the values provided by the input layer neurons  $x_1, x_2, x_3, \dots, x_j$  to the  $i^{th}$  hidden neuron are considered to be already normalized.

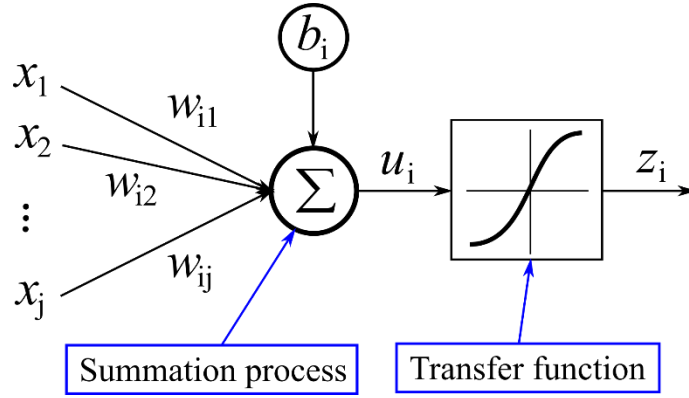


**Figure 7:**  $i^{th}$  single neuron structure belonging to the ANN hidden layer.

The number of neurons for the hidden and output layer are denoted by “ $k$ ” and “ $l$ ”, respectively (i.e.,  $z_1, z_2, z_3, \dots, z_k$  and  $y_1, y_2, y_3, \dots, y_l$ ). The process that takes place in the hidden and output layer neurons is explained using Figure 7 and equation 2.2.

$$u_i = \sum_{n=1}^j w_{in} \cdot x_n + b_i \quad (2.2)$$

The  $i^{th}$  neuron belonging to the hidden layer (i.e.,  $z_i$ ) is used to describe the computation process. The first operation made by the neuron is the weighted summation

of the inputs (i.e., output values from the neurons of the previous layer, which in this case, are the normalized inputs of the problem) plus a value called “bias”. The result of this operation is denoted by  $u_i$ . This value constitutes the independent variable (i.e., input) for the transfer function  $f(\cdot)$  of the neuron.

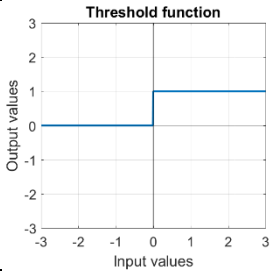
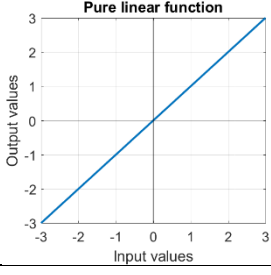
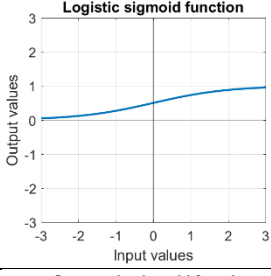
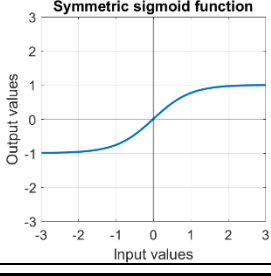
$$z_i = f(u_i) \quad (2.3)$$

The transfer function, also called the activation function, has two main objectives: The first one is to map the results of the weighted summation within a fixed range (mainly for neurons belonging to hidden layers). The second objective is to give the neural network linear or nonlinear behavior. Transfer functions such as logistic sigmoid and symmetric sigmoid are commonly implemented in the hidden layer neurons. The reason is explained later in the training subsection 2.1.3. The output for the  $i^{th}$  neuron of the hidden layer is denoted by  $z_i$ . This value represents the input from the  $i^{th}$  neuron to all the output layer neurons. The same computation process explained for the hidden layer takes place on the output layer. The implemented transfer function for the output layer neurons could or could not be different from the hidden layer neurons. In the current thesis, the implementation of different transfer functions for the hidden and output layers neurons was investigated.

### 2.1.2 ANN transfer functions

The neurons transfer functions implemented on the different layers defines how the ANN will behave. There are many different transfer functions. Table 5 shows four examples of activation functions, how they are defined, example plots and their objectives when implemented on ANNs.

Table 5: ANN transfer functions

| Transfer function                      | Definition                                                                            | Figure                                                                               | Implementation                                                                                                                                                                                                                                                                               |
|----------------------------------------|---------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Threshold                              | $y_{(x)} = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$ |    | The threshold transfer function is usually implemented on the output neurons for ANNs performing classification tasks. The possible outputs of this function are 0 or 1.                                                                                                                     |
| Pure linear                            | $y_{(x)} = x$                                                                         |    | The pure linear transfer function is commonly used for output layer neurons of ANNs which main purpose is curve fitting. The trained ANN shows an unconstrained behavior (there is no lower or upper limit for future test cases).                                                           |
| Logistic sigmoid                       | $y_{(x)} = \frac{1}{1 + e^{-x}}$                                                      |   | The logistic sigmoid function is commonly used for hidden neurons. It has a saturated behavior for large negative and positive values (asymptotes on 0 and 1, respectively). The outputs are mapped to the range of [0;+1] It gives the ANN the capability to deal with non-linear problems. |
| Symmetric sigmoid (hyperbolic tangent) | $y_{(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$                                         |  | The symmetric sigmoid function is mostly used for hidden neurons. It has the same behavior than the logistic sigmoid, but the asymptotes are -1 and 1. The outputs are within the range of [-1;+1]. It also provides a non-linear behavior to the ANN.                                       |

When the main purpose of the ANN is curve fitting, there are two combinations of transfer function typically implemented:

1. A logistic sigmoid activation function for the hidden layers neurons and a pure linear transfer function for the output layer neurons.
2. A symmetric sigmoid transfer function for the hidden layers neurons and a pure linear transfer function for the output layer neurons.

Both logistic sigmoid and symmetric sigmoid transfer functions provide the ANN with the capability to deal with non-linear problems. The usage of these functions on the hidden

layer is closely related to the training process. The need for smooth and continuous functions is related to the back-propagation algorithm used during the ANN training. This algorithm is explained later in subsection 2.1.4.

### 2.1.3 ANN training process

Different ANN training methods can be found in the literature. Error-Correction, Hebbian Learning, Competitive Learning, etc. However, the Supervised Learning method (closely related to the error correction method) is commonly used for ANN training. During the training process, the ANN is presented with experimental data consisting of both inputs and target values (also called “desired outputs”). Figure 8 shows a schematic of the supervised learning process.

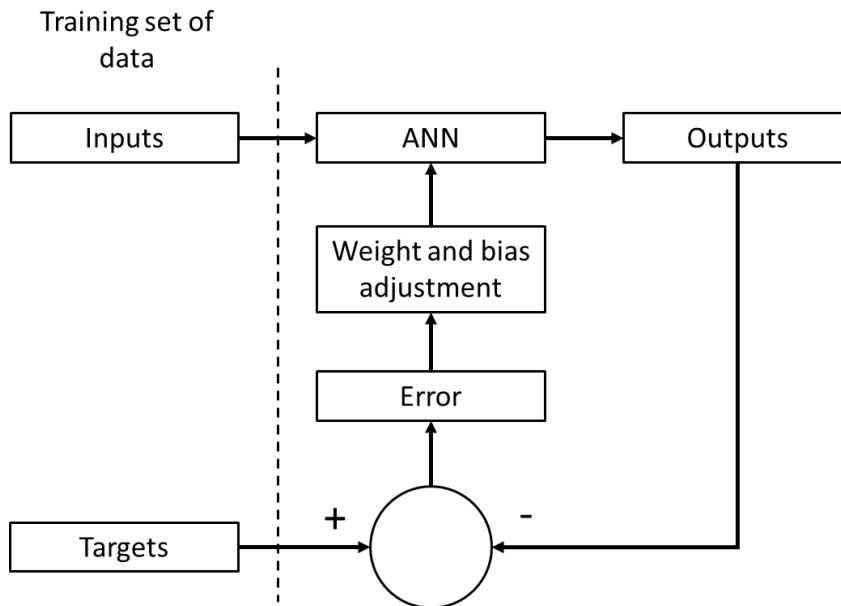


**Figure 8:** Schematic of the ANN supervised learning process.

The steps to train the ANN under a supervised learning process are as follows:

1. The experimental data is divided into two main subsets: i) a training set and ii) a test set. The latter is mainly used for validation purposes.
2. The neuron weights and biases are assigned initial values.

3. The training set is presented to the ANN on the first training iteration (also denoted as epoch). The ANN produces a set output values corresponding to the input data set.
4. The error between the outputs for the current training epoch and targets is computed.
5. The weights and biases values are updated based on the error obtained in the first iteration (using the back-propagation algorithm, which is explained in subsection 2.1.4).
6. Once again, the training data is presented to ANN on a second iteration step, producing a new set of outputs.
7. Steps 4 and 5 are repeated, and a new weight and bias adjustment is performed.
8. The training finishes when a stop criteria is met. This stopping criteria could involve a minimum target error, a maximum number of iterations, cross-validation, etc.

Although ANNs are powerful tools to model complex problems, there is a risk of overfitting the training data during the ANN developing (i.e., the ANN loses the generalization capability). An example of overfitting training data is presented in Figure 9.

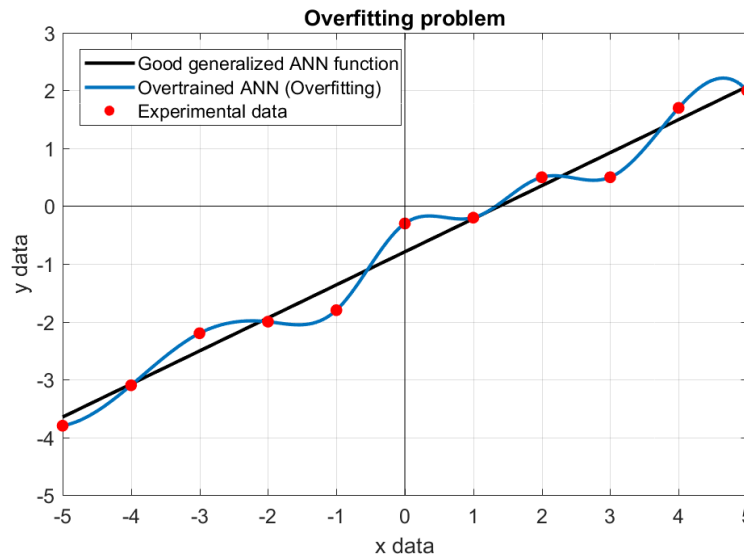


**Figure 9:** Example of overtraining of ANN.

In this thesis, the cross-validation early stop criteria was adopted to avoid overfitting. In order to apply this stop criteria, the training set is once again divided into two subsets: i) the first one is still being used to train the ANN (weights and biases adjustments to minimize the error) and ii) a second set called the validation set. The validation set is not used for the training process itself. Still, for each epoch (i.e., training iteration), the error between the outputs and the targets of the validation set is computed. Figure 10 shows an example of the mean squared error obtained at each epoch during an ANN training in MATLAB.

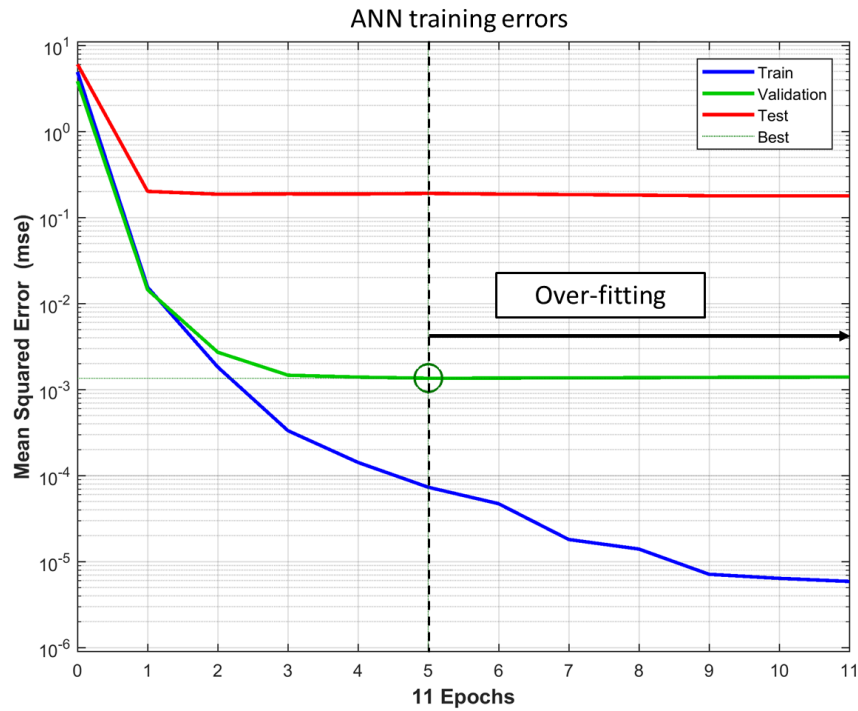


**Figure 10:** Validation step early stop criteria example (ANN training in MATLAB).

It can be observed that the mean squared error for the training set is steadily dropping during the training process. The error computed for the validation set follows the same decreasing trend for a certain number of iterations. In this example, the validation set error reaches a minimum value on epoch 5. In Figure 10, after reaching a minimum, the validation set error slightly increases for epoch 6, and remains constant for the rest of the subsequent training epochs. In other words, the validation error stops decreasing after epoch 5. If, after reaching a minimum value, the validation error does not decrease for a user-

defined finite number of iterations, the training will stop. In this example, if the validation error does not reduce for six consecutive epochs, the training stops. It is clear that the error computed for the training set is still reducing, even after epoch 5. This is a clear sign that the ANN is over fitting the training data set and losing the generalization capability. The training stops in epoch 11. The final ANN weights and biases values adopted in this case are the ones from epoch 5, which provided the minimum validation error during the training.

#### 2.1.4 *Back-propagation algorithm*

It has been shown that in ANN models there are many free parameters (neuron weights and biases). These parameters are adjusted during the ANN training in order to decrease the error between outputs and targets (experimental data). The adjustment of the free parameters can be done in different ways. For this thesis, the *back-propagation algorithm* is adopted.

This algorithm has one important advantage: the gradient of the error computed in the output layer with respect to any weight of any neuron present in the ANN can be traced back. Using this algorithm, the weights and biases are updated in the gradient direction and not following an arbitrary direction. It saves time and computational effort. The implementation of this algorithm for ANN training creates certain requirements on the activation functions implemented on the neurons.

The following back propagation algorithm derivation was obtained from Simon Haykin's book (1994). The example for the  $n^{th}$  neuron belonging to the output layer is used to explain the back propagation algorithm, as illustrated in Figure 11.

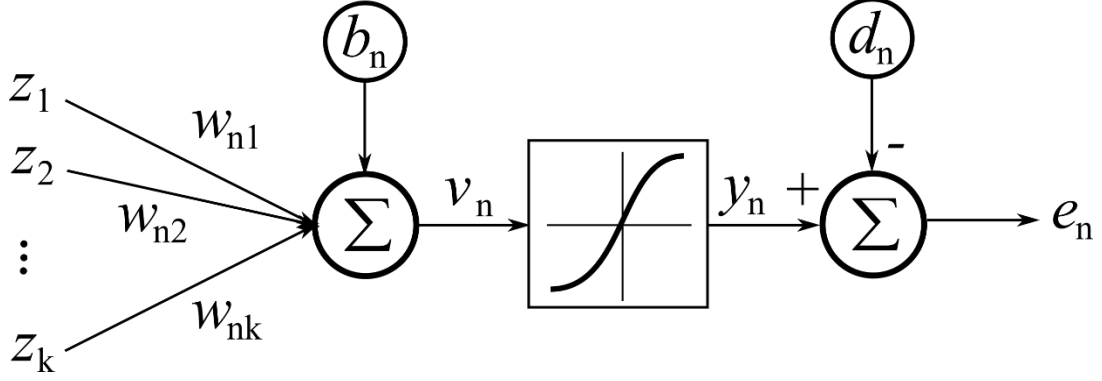


**Figure 11:** Error computation for the  $n$ th neuron belonging to the output layer.

Equation 2.4 shows the computation for the  $n^{th}$  neuron belonging to the output layer. It is the same calculation presented in equation 2.2, but instead of a hidden neuron, this represents an output neuron.

$$v_n = \sum_{i=1}^k w_{ni} \cdot z_i + b_n \quad (2.4)$$

In equation 2.4,  $w_{ni}$  represents the weight applied to the input value  $z_i$  coming from the  $i^{th}$  neuron of the hidden layer to the  $n^{th}$  neuron of the output layer.  $b_n$  represents the bias value corresponding to the  $n^{th}$  neuron of the output layer. The error computed on the  $n^{th}$  neuron is given by:

$$e_n = d_n - y_n \quad (2.5)$$

In equation 2.5,  $d_n$  represents the desired output (target value provided by the training data) and  $y_n$  represents the actual output of the neuron. The latter is obtained with the current epoch weights and biases. The total squared error obtained in the output layer is computed as the summation of the error of all the output neurons.

$$E(q) = \frac{1}{2} \sum_{n=1}^l e_n^2 \quad (2.6)$$

The total error is computed for each sample  $q$  of inputs/targets belonging to the training set. The range of  $q$  goes from 1 until the number of samples present in the training set (denoted with the letter  $N$ ). Then the total squared error computed in equation 2.6 is divided by the number of samples  $N$  to obtain an average error.

$$E_{avg} = \frac{1}{N} \sum_{q=1}^N E(q) \quad (2.7)$$

$E_{avg}$  represents the cost function to be minimized during the learning process of the ANN.  $E_{avg}$  is a function of the weights and biases present in the ANN neurons. Following the notation presented in Figure 11, the values of  $v_n$  and  $y_n$  are computed following equations 2.4 and equation 2.9 (a single training set sample is considered).

$$y_n = f(v_n) \quad (2.8)$$

The back propagation algorithm looks for a correction  $\Delta w_{ni}$  in order to minimize the error between the outputs and targets. The weight correction is proportional to the instantaneous gradient of the total error with respect to  $w_{ni}$ . Applying the chain rule, we get:

$$\frac{\partial E}{\partial w_{ni}} = \frac{\partial E}{\partial e_n} \frac{\partial e_n}{\partial y_n} \frac{\partial y_n}{\partial v_n} \frac{\partial v_n}{\partial w_{ni}} \quad (2.9)$$

This gradient represents the direction of search in the weight space. Differentiating both sides of equation 2.6 with respect to  $e_n$ :

$$\frac{\partial E}{\partial e_n} = e_n \quad (2.10)$$

Differentiating equation 2.5 with respect to  $y_n$ :

$$\frac{\partial e_n}{\partial y_n} = -1 \quad (2.11)$$

Differentiating equation 2.8 with respect to  $v_n$

$$\frac{\partial y_n}{\partial v_n} = \frac{\partial f(\cdot)}{\partial v_n} \quad (2.12)$$

Lastly, we differentiate equation 2.4 with respect to the  $w_{ni}$  weight:

$$\frac{\partial v_n}{\partial w_{ni}} = z_i \quad (2.13)$$

Therefore, when replacing equations 2.10 through 2.13 into equation 2.9, we obtain:

$$\frac{\partial E}{\partial w_{nj}} = -e_n \cdot \frac{\partial f(\cdot)}{\partial v_n} \cdot z_j \quad (2.14)$$

The correction  $\Delta w_{ni}$  is computed using the delta rule:

$$\Delta w_{ni} = -\eta \frac{\partial E}{\partial w_{ni}} \quad (2.15)$$

In equation 2.16,  $\eta$  is denominated learning-rate parameter, and it determines the rate of learning in the back-propagation algorithm. Replacing equation 2.14 in 2.15 gives:

$$\Delta w_{ni} = \eta \cdot e_n \frac{\partial f(\cdot)}{\partial v_n} z_i \quad (2.16)$$

Defining the local gradient  $\delta_n$  as:

$$\delta_n = e_n \cdot \frac{\partial f(\cdot)}{\partial v_n} \quad (2.17)$$

Replacing equation 2.17 in equation 2.16, we obtain:

$$\Delta w_{ni} = \eta \cdot \delta_n \cdot z_i \quad (2.18)$$

Equations 2.17 and 2.18 show that the error computed in the  $n^{th}$  neuron, and its activation function, play major roles in the weight correction process to minimize the error. Implementing the back-propagation algorithm for free parameters adjustment requires the activation function present in the neurons to be differentiable.

## 2.2 Non-negative ANN configuration

ANNs are used to deal with a wide variety of problems presenting properties such as high complexity, high number of variables, non-linearity, etc. There is also multiple ways to configure ANNs. Each configuration responds to the specific needs of the problem to be modeled. In this thesis, the main objective is to investigate and create a specific ANN configuration to predict acoustic sound pressure values. This objective demands the ANN to predict only positive values. More details on the requirements and derivation of such

configuration are explained. Moreover, multiple configurations will be presented and discussed in this section.

### 2.2.1 ANN configuration for curve fitting problems

The ANN for curve fitting purposes presented as an example uses a symmetric sigmoid transfer function on the hidden layer neurons and a pure linear transfer function on the output layer neurons, as shown in Table 5 in subsection 2.1.2. The following notation is used to explain how this ANN performs when only positive output values are desired:

1. The inputs are denoted as  $x_1, x_2, x_3, \dots, x_j$ .
2. The outputs are denoted as  $y_1, y_2, y_3, \dots, y_l$ .
3. The maximum and minimum values of the outputs generated by the ANN are denoted as  $y_{\max}$  and  $y_{\min}$ .
4. The targets are denoted as  $t_1, t_2, t_3, \dots, t_l$ , and are considered to be strictly positive.
5. The maximum and minimum values of the targets used to train the ANN are denoted as  $t_{\max}$  and  $t_{\min}$ .

The first step during the training process is to normalize the input and target values within the range  $[-1; +1]$  following equation 2.1. Hence, the outputs generated by the ANN will be within the range of  $[t_{\min}; t_{\max}]$ , as shown in Figure 12. It can be clearly seen that the lowest value -1 corresponds to the lowest target value present in the training set, while the value +1 corresponds the highest one. This information is superposed with the linear transfer function adopted in the output layer neurons.

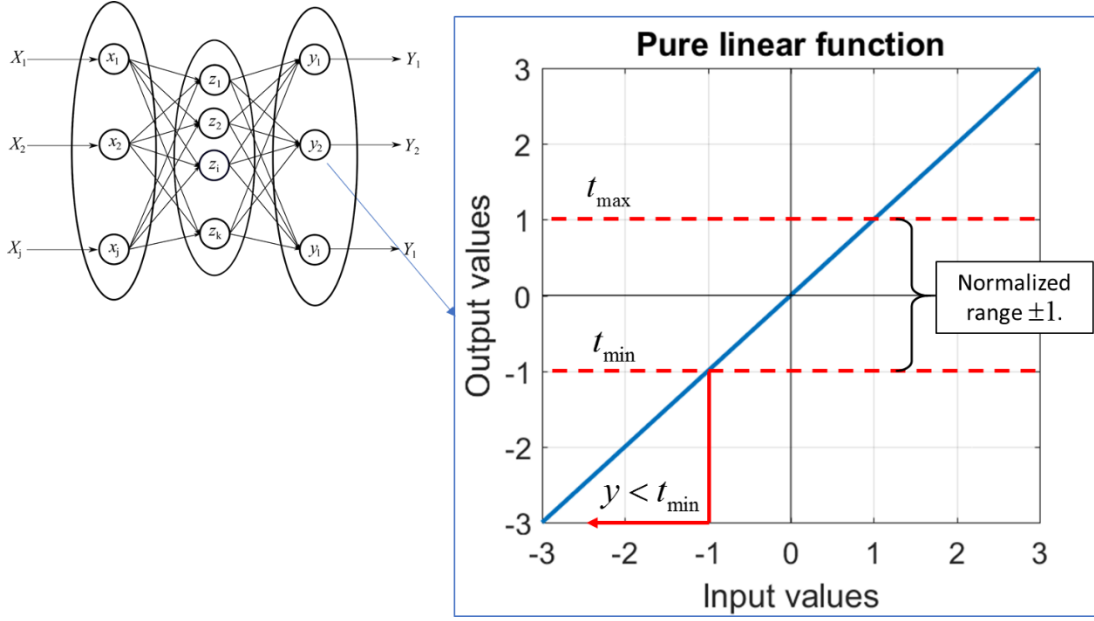


**Figure 12:** Pure linear transfer function implemented in the output layer.

Once the ANN is trained, given a new set of inputs (i.e., set of data never used during the training process), the ANN can produce output values below  $t_{\min}$ . The pure linear activation function does not have a lower or an upper limit. This allows the trained ANN to predict values below the lowest target value present in the training set. Also, it allows to get output values above the highest value present in the training set. Even if the target values given during the training are all positive, the ANN is able to produce negative output values. How often the ANN predicts negative values depends on the problem. It can be concluded that if only positive outputs are desired, the commonly used curve-fitting configuration will not fulfill the only-positive outputs requirement.

### 2.2.2 ANN configuration for positive outputs - constrained

A second configuration is investigated, where the pure linear transfer function in the output layer is replaced by a symmetric sigmoid activation function. Figure 12 shows the schematic with the targets normalization process for this configuration.

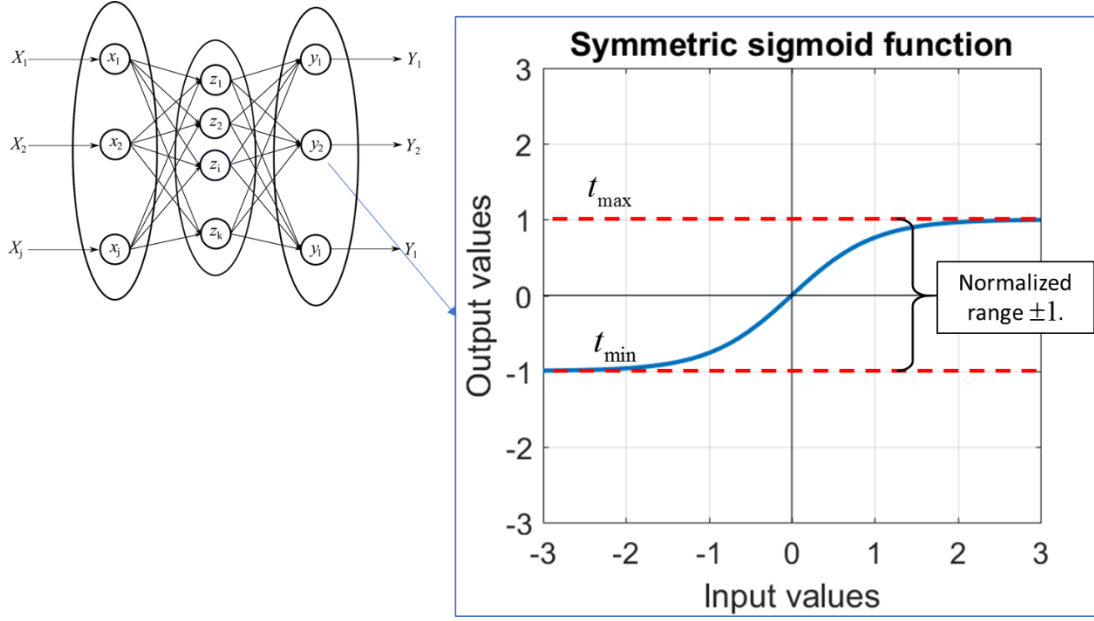


**Figure 13:** Symmetric sigmoid transfer function implemented in the output layer.

In this case, the trained ANN will be able to produce results only within the  $[t_{\min}; t_{\max}]$  range. Moreover, the lowest value that the ANN can predict is  $t_{\min}$ . Making the assumption that the lowest target value  $t_{\min}$  present on the training set is positive, it is accurate to say that the trained ANN will produce only positive values in future test cases. However, this configuration also generates a constrain on the ANN outputs. The same logic for the minimum possible predicted value is applied for the upper limit. The highest value that the trained ANN can predict is  $t_{\max}$ . As long as the target values present in the training set are only positive, this configuration can be considered as a non-negative outputs configuration. Nevertheless, even though the negative outputs problem is solved, the trained ANN will have an upper limit for future predictions.

### 2.2.3 Unconstrained ANN configuration for positive outputs

A third configuration is proposed and studied. It was observed from the second configuration investigated that the implementation of saturated functions on the output layer neurons creates restrictions on the output range. A lower limit is desired to avoid negative outputs. On the other hand, an upper limit for the ANN is not preferred. This

provides requirements that an ideal transfer function on the output layer should comply. In order to fulfill such requirements, a hybrid transfer function is proposed for the output layer neurons:

$$y_{(x)} = \begin{cases} x & \text{if } x \geq 0 \\ \frac{e^x - e^{-x}}{e^x + e^{-x}} & \text{if } x < 0 \end{cases} \quad (2.19)$$

This transfer function results from a combination of a symmetric sigmoid transfer function for input values below 0, and a pure linear transfer function for values equal or higher than 0. Figure 14 shows the normalization logic applied to the proposed hybrid activation function. Assuming that the target values present on the training set are positive, then the trained ANN will have the properties of:

1. The lowest possible predicted value will be the lowest target value present in the training set (i.e.,  $t_{\min}$ ). Hence, it will always be positive.
2. The highest value predicted can be any positive value. Therefore, the trained ANN has no upper limit for possible future predictions.

Then, along with the non-negative property given by the symmetric sigmoid function for the negative inputs, the upper limit that a saturated function such as the one implemented in the previous configuration is overcome.

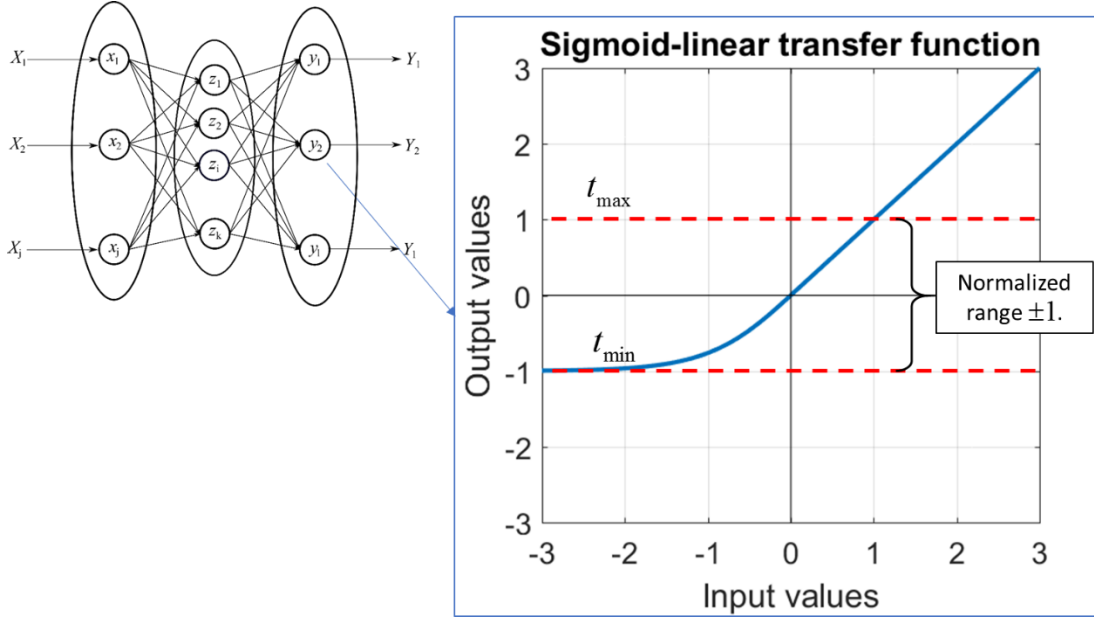


**Figure 14:** Hybrid transfer function implemented in the output layer.

Finally, it must be proven that the hybrid transfer function is differentiable in order to implement the back-propagation algorithm during the ANN training. Separately, the symmetric sigmoid and the pure linear functions are differentiable. Still, the case where the input to the hybrid function is equal to zero must be analyzed. It is clear that both functions tend to the zero at  $x = 0$ . In order to assure that the derivative of the function is continuous, the left and right hand side derivatives are computed and compared:

$$f'(0^-) = \text{sech}(0) = \frac{2}{e^0 + e^{-0}} = \frac{2}{2} = 1 \quad (2.20)$$

$$f'(0^+) = 1 \quad (2.21)$$

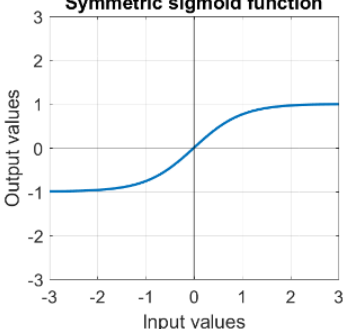
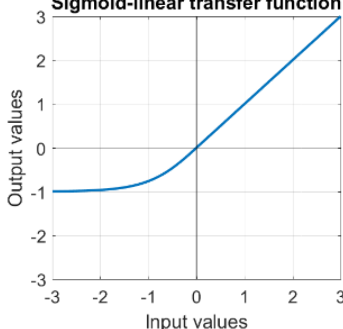
The hybrid function is differentiable. Hence, it is applicable for the back-propagation algorithm.

### 2.2.4 ANN configuration for noise prediction

Let us consider the case where an ANN is implemented to predict TPIN. Without going into details regarding the possible inputs to such model, it is accurate to say that the outputs of the ANN are related to sound. Sound is defined as the fluctuation of pressure around the atmospheric pressure. It is commonly described using the acoustic sound pressure is defined as

$$p_{rms}^2 = \sqrt{\frac{1}{T} \int_0^T [p(x, t) - \bar{p}(x)]^2} \quad (2.22)$$

where  $p(x, t)$  represents the instantaneous pressure,  $T$  is the period of time considered, and  $\bar{p}(x)$  is the average pressure. Equation 2.22 shows that  $p_{rms}^2$  will always be a positive number. Therefore, a suitable ANN configuration to predict  $p_{rms}^2$  values is shown in Table 6. This configuration was implemented in the model to predict TPIN.

| Table 6: ANN configuration for noise prediction                                                                              |                                                                                                                                    |                                                                                                                                                                          |
|------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Hidden layers transfer function                                                                                              | Output Layer transfer function                                                                                                     | Outputs                                                                                                                                                                  |
| <p><b>Symmetric sigmoid function</b></p>  | <p><b>Sigmoid-linear transfer function</b></p>  | <p>Assuming the targets values used to train the ANN are <math>p_{rms}^2</math> (i.e., only positive), then the outputs generated by the ANN will always be positive</p> |

### 3 Pavement parameters related to TPIN

Tire noise is the only vehicle noise component that is strongly related to an external factor such as the pavement surface. Quiet tires and quiet pavements have been studied separately. However, the generated noise is a function of the interaction of both parts: tire and pavement (Thrasher et al., 1976). In this chapter, we introduce the main parameters used to characterize the pavement surface. Some of them have been previously related to TPIN. Then, the experiments to collect tire noise and pavement profile data on different pavements are presented (U.S. Route 460 and VTTI SMART Road). Moreover, both tire noise and pavement data processing results are shown. Finally, the processed tire noise and pavement profile data is used to provide insight, and draw conclusions on the relationship between TPIN and the pavement surface.

#### 3.1 Pavement surface terminology

The World Road Association defines texture as “surface irregularities of a road pavement with horizontal dimensions ("wavelengths") ranging between 0 and 500 mm” (PIARC 2018, road dictionary, retrieved from internet). Figure 15 shows the different texture categories, and their influence on the pavement surface characteristic. Road textures are classified by the standard ISO 13473-2:2002 as:

- Megatexture: The wavelength range considered in this category is 50-500 mm. This texture level is a product of road wear (i.e., potholes and pavement distress among others) or road construction characteristics. It is mainly reflected on the vehicle ride quality. It affects the in-vehicle vibrations and has some influence on the exterior vehicle noise (TPIN).
- Macrotexture: The wavelength range considered for this category is 0.1-20 mm. This specific texture range becomes the most important feature for vehicle-pavement interaction characteristics such as wet weather friction, tire-pavement interaction noise, and splash and spray.
- Microtexture: The wavelength range considered for this category is  $1\ \mu\text{m}$ -0.5 mm. This road texture range is represented by the surface properties of the aggregate

which is in direct contact with the tire. It is strongly related to the pavement surface friction. However, it is not related to TPIN nor to the splash and spray properties of the pavement.

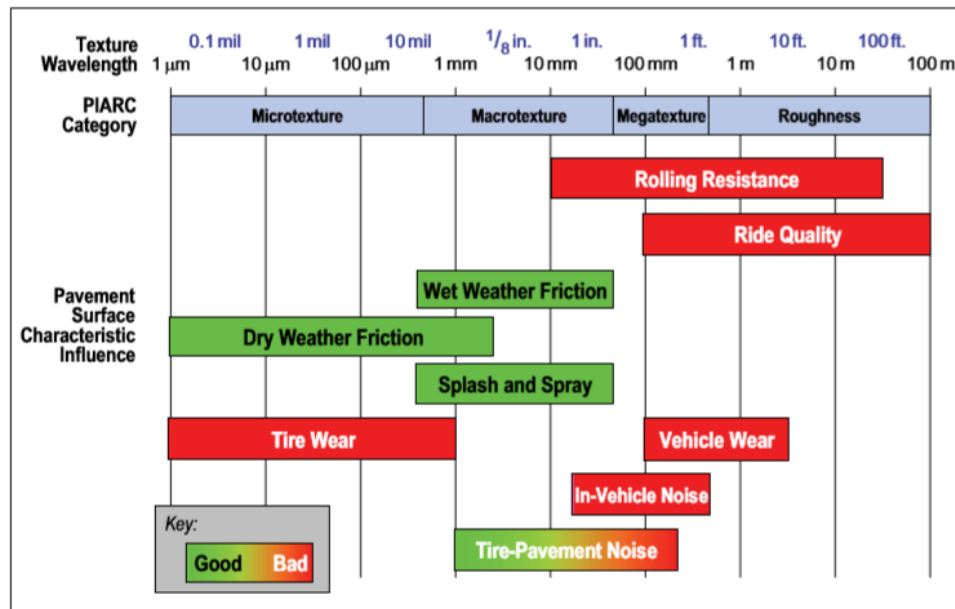


**Figure 15:** Pavement surface classifications and association with vehicle-pavement interaction characteristics. (ISO 13473-2:2002)

Texture wavelengths longer than 500 mm are referred to as pavement roughness, also called unevenness. They relate poorly with vehicle-pavement interactions. They are more related to the dynamics of the vehicle.

## 3.2 Experiments

This section presents the experiments carried out at the U.S. Route 460 road and at the Virginia Tech Transportation Institute (VTTI) SMART road. Tire noise data was collected for different tires on different pavement surfaces. In addition, the pavement profile data was obtained using a scanning laser mounted on a SCRIM (Sideway-force Coefficient Routine Investigation Machine) truck.

### 3.2.1 Equipment

The equipment used for measuring tire noise was an OBSI system. Figure 16 shows the OBSI setup and microphone denomination. The acquisition system used for testing has a sampling frequency of 25.6 kHz. As it was shown before (see Figure 2), the OBSI counts with an optical sensor to acquire the tire one-per-revolution signal. During the post processing, the TPN and the NTPN components were obtained using the tire noise separation concept (Feng, 2017). The noise data used for this study corresponds to the leading inboard microphone (i.e., mic 1) of the OBSI system.

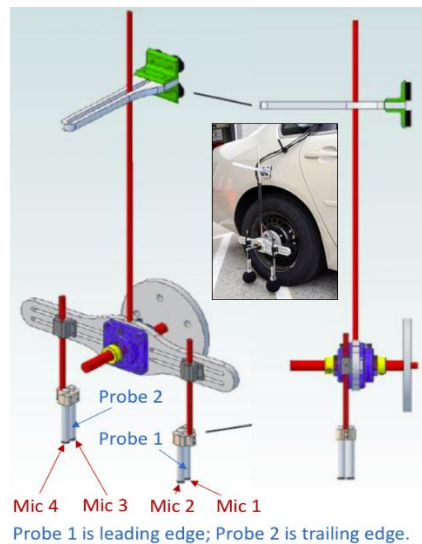


**Figure 16:** OBSI system schematic and microphone denomination.

Figure 17 shows a picture of the SCRIM truck (owned by VTTI) used to obtain the pavement profile data. It is equipped with a scanning laser with a sampling frequency of

64 kHz. The pavement surface data was provided by the Center for Sustainable Transportation Infrastructure (CSTI) at VTTI. The profile was sampled to a spatial resolution of:

- 0.5 mm in the case of the SMART road, and
- 0.98 mm for the US460 road.



**Figure 17:** Sideway-Force Coefficient Routine Investigation Machine (SCRIM) equipped with a scanning laser (sampling frequency 64 kHz) used to measure the pavement profile.

The experimental results for each test location are presented and discussed later in this thesis.

### *3.2.2 Roads tested*

Two locations were tested: U.S. Route 460 road and at the VTTI SMART road. Table 7 shows the information of the experiments that were carried out at the U.S. Route 460. Different steady state vehicle speeds were tested. In addition, an acceleration test was conducted. Tire noise was collected on both eastbound and westbound directions. However, pavement profile data was collected only on the eastbound lane. This thesis focuses only on the data collected for the eastbound lane of the U.S. Route 460 road.

| Table 7: U.S. Route 460 road test information |                                                                                                                    |
|-----------------------------------------------|--------------------------------------------------------------------------------------------------------------------|
| Pavement and tires tested                     |                                                                                                                    |
| Pavement                                      | 1 - Dense graded hot mix asphalt (HMA)                                                                             |
| Number of tires                               | 42 tires (26 all-season, 8 winter tires, 1 SRTT tire, 1 spare tire, 1 worn tire, 1 concept tire, and 1 slick tire) |
| Tread pattern rubber hardness range           | 56 – 79 Shore A                                                                                                    |
| Test conditions                               |                                                                                                                    |
| Steady state speeds                           | 45 50 55 60 65 mph                                                                                                 |
| Acceleration test                             | 45 to 65 mph                                                                                                       |
| Tire pressure                                 | 26 32 40 psi                                                                                                       |
| Temperature range                             | 37°F to 86°F                                                                                                       |
| Vehicles                                      |                                                                                                                    |
| Tire diameter < 700 mm                        | 2012 Chevrolet Impala (FWD)                                                                                        |
| Tire diameter < 700 mm                        | 2017 Chevrolet Tahoe (AWD)                                                                                         |

The test section where tire noise data was collected is shown in Figure 18. The pavement profile was acquired for a larger section (the amount of data corresponds to approximately 3.9 km).

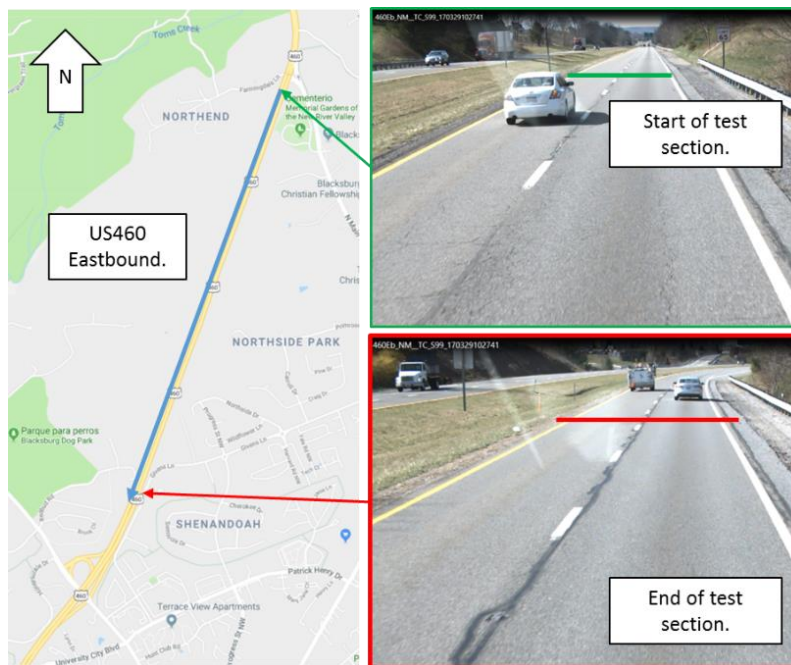


**Figure 18:** U.S. Route 460 road eastbound test section.

In the case of the SMART road, tire noise data was collected for different tires at different pavement surfaces. Different steady state vehicle speeds were tested. No acceleration test was conducted. Table 8 shows the information of the experiments carried

out at the VTTI SMART road. Tire noise data was collected on the uphill direction (the downhill direction was not tested due to limited time availability to use the road). In addition, pavement profile data was obtained using the same SCRIM truck shown in Figure 17.

| Table 8: VTTI SMART road test information |                                                                                                                                                                                    |
|-------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Pavement and tires tested                 |                                                                                                                                                                                    |
| Pavement                                  | 28 (14 surface mixes asphalts, 8 concrete, 3 bridges, 1 open graded friction course, 1 concrete section with longitudinal grooves and 7 concrete sections with transverse grooves) |
| Number of tires                           | 5 tires (2 winter tires, 1 SRTT tire and 2 all-season tires)                                                                                                                       |
| Tread pattern rubber hardness range       | 63 – 75 Shore A                                                                                                                                                                    |
| Test conditions                           |                                                                                                                                                                                    |
| Steady state speeds                       | 45 50 55 60 mph                                                                                                                                                                    |
| Tire pressure                             | 32 psi                                                                                                                                                                             |
| Temperature range                         | 66°F to 72°F                                                                                                                                                                       |
| Vehicles                                  |                                                                                                                                                                                    |
| Tire diameter < 700 mm                    | 2015 Chevrolet Impala (FWD)                                                                                                                                                        |

Figure 19 shows a simplified schematic graph of the different pavement sections present in the SMART road (information provided by VTTI). The pavement sections denomination are as follows:

- Regular Surface Mixes (SM) sections are denoted with a letter (except for sections K and L1). They are dense graded mixes with a uniform distribution of aggregate sizes. According to the Virginia Department of Transportation (VDOT), they are commonly used for both structural and functional purposes (exposed to traffic). The number that follows denotes the nominal maximum aggregate size (e.g., SM-4.75, SM-9.0, SM-9.5, SM-12.5, etc.). We point out that SM-9.5 is recommended for most final surface applications in the state of Virginia (VDOT).
- Portland Cement Concrete (PCC) pavement surfaces sections are denoted with PCC followed by a number and a letter.
- Section L1 is a Stone Matrix Asphalt (SMA) pavement section. It is a gap graded mix, where the distribution of aggregate sizes is non-uniform.
- Section K is an Open Graded Friction Course (OGFC). They are designed to be water permeable. They have a very low content of fine aggregate material to allow

water drainage. In addition, It has been reported that the presence of a high percentage of air voids considerably diminishes TPIN (Sandberg et al., 2002).

The data of the SMART road pavement profile was provided as:

1. One file containing the profile for the entire SMART road track.
2. Twenty eight different files containing the pavement profile for each section of the road.

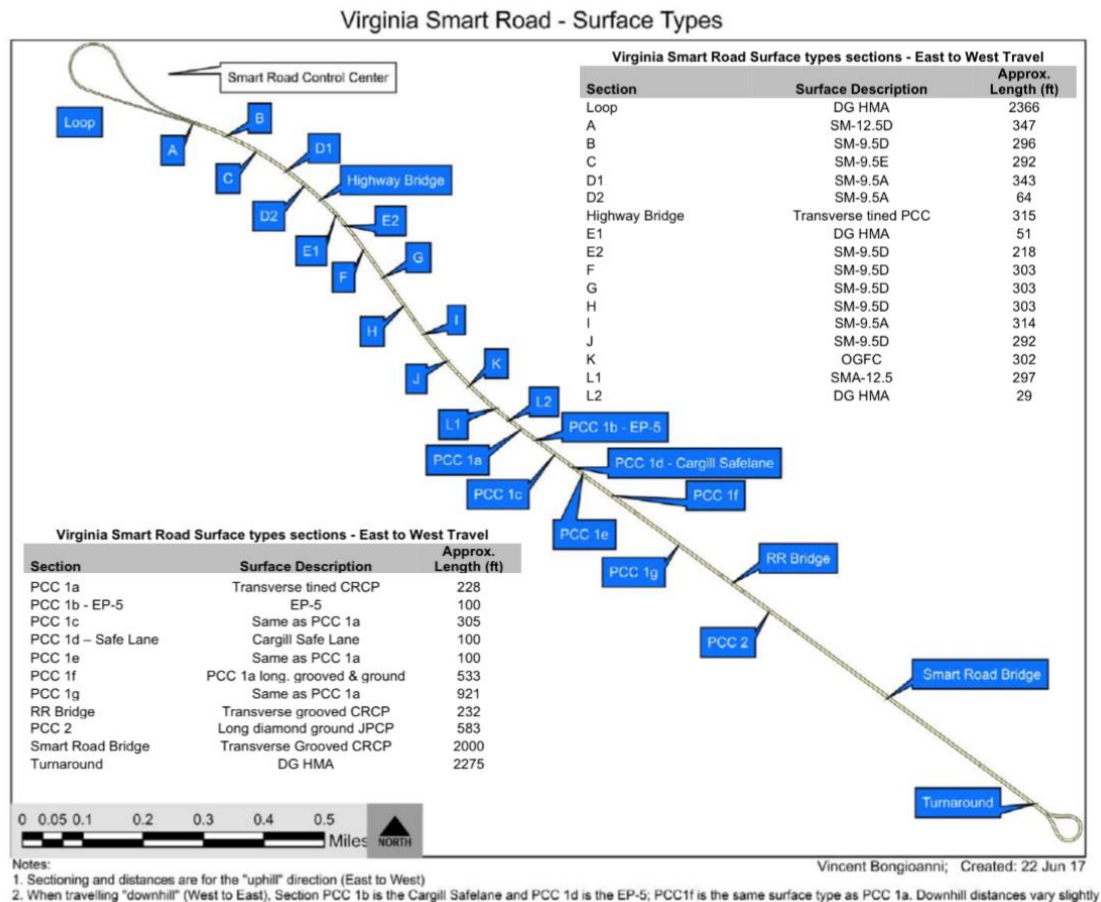


**Figure 19:** VTTI SMART road pavement sections.

Some aspects regarding the tire noise data collection are highlighted:

- Due to limitations in the time available to test, tire noise data was acquired only for the "uphill" lane (i.e., right to left direction in Figure 19).

- Tire noise for the pavement sections corresponding to the roundabouts on the track endings was not acquired (the vehicle speed had to be reduced when approaching them).
- For certain runs, tire noise for the pavement sections at the end of the track was not recorded (mainly sections A through D).
- Tire noise data was obtained as one single file for the entire track.
- The optical sensor signal was used to compute the TPN and NTPN components for each run.

### 3.2.3 *Tires tested*

Forty-two tires were tested at the U.S Route 460. Along the tested tires there were:

- Multiple all-season tires
- Multiple winter tires
- The Standard Reference Test Tire (SRTT)
- One competition tire (slick)
- Two tires that are not for sale
- One spare tire

Details of the tires tested are shown in Table 9 below. Pictures of the tread patterns of the tires tested, the vehicles and the setup to collect tire noise data at the U.S. Route 460 are shown in Figure 20.

Table 9: U.S. Route 460 road test tires information

| Tire number | Condition          | Size      | Width (mm) | Outer diameter (mm) | Rubber hardness* |
|-------------|--------------------|-----------|------------|---------------------|------------------|
| 01          | All-season         | 215/60R16 | 215        | 664.4               | 73.0             |
| 02          | All-season         | 215/60R16 | 215        | 664.4               | 63.3             |
| 03          | All-season         | 215/60R16 | 215        | 664.4               | 67.5             |
| 04          | All-season         | 215/60R16 | 215        | 664.4               | 66.5             |
| 05          | All-season         | 215/60R16 | 215        | 664.4               | 68.5             |
| 06          | All-season         | 215/60R16 | 215        | 664.4               | 64.5             |
| 07          | All-season         | 215/60R16 | 215        | 664.4               | 70.3             |
| 08          | All-season         | 215/60R16 | 215        | 664.4               | 63.7             |
| 09          | Winter             | 215/60R16 | 215        | 664.4               | 59.0             |
| 10          | All-season         | 215/60R16 | 215        | 664.4               | 63.7             |
| 11          | All-season         | 215/60R16 | 215        | 664.4               | 61.7             |
| 12          | Winter             | 215/60R16 | 215        | 664.4               | 57.5             |
| 13          | All-season         | 215/60R16 | 215        | 664.4               | 64.3             |
| 14          | All-season         | 215/60R16 | 215        | 664.4               | 64.0             |
| 15          | All-season         | 215/60R16 | 215        | 664.4               | 56.5             |
| 16          | All-season         | 215/60R16 | 215        | 664.4               | 67.0             |
| 17          | All-season         | 215/60R16 | 215        | 664.4               | 59.3             |
| 18          | All-season         | 215/60R16 | 215        | 664.4               | 65.8             |
| 19          | Winter             | 215/60R16 | 215        | 664.4               | 66.0             |
| 20          | <b>SRTT</b>        | 225/60R16 | 225        | 676.4               | 72.0             |
| 21          | Competition        | 225/60R16 | 225        | 676.4               | 56.0             |
| 22          | All-season         | 225/60R16 | 225        | 676.4               | 75.0             |
| 23          | All-season         | 225/60R16 | 225        | 676.4               | 65.0             |
| 24          | Winter             | 215/60R16 | 215        | 664.4               | 65.3             |
| 25          | Winter             | 215/60R16 | 215        | 664.4               | 67.3             |
| 26          | Winter             | 215/60R16 | 215        | 664.4               | 59.0             |
| 27          | Winter             | 215/60R16 | 215        | 664.4               | 68.0             |
| 29          | Winter             | 215/60R16 | 215        | 664.4               | 66.8             |
| 35          | Bald               | 265/70R17 | 265        | 802.8               | 77.0             |
| 37          | All-season         | 265/70R17 | 265        | 802.8               | 71.5             |
| 39          | Not for sale       | 255/55R18 | 255        | 737.7               | 76.5             |
| 41          | Bald (LT)          | 235/85R16 | 235        | 805.9               | 72.0             |
| 42          | All-season (LT)    | 235/85R16 | 235        | 805.9               | 72.0             |
| 43          | All-season         | 215/60R16 | 215        | 664.4               | 70.0             |
| 45          | All-season         | 235/55R19 | 235        | 741.1               | 71.0             |
| 46          | <b>SRTT (Worn)</b> | 225/60R16 | 225        | 676.4               | 76.0             |
| 49          | Not for sale       | 205/70R15 | 205        | 668.0               | 74.0             |
| 53          | Trailer            | 235/80R16 | 235        | 782.4               | 79.0             |
| 54          | All-season         | 245/40R18 | 245        | 653.2               | 68.5             |
| 55          | All-season         | 235/70R16 | 235        | 735.4               | 61.5             |
| 56          | Spare              | 125/70R16 | 125        | 581.4               | 75.0             |
| 57          | Worn               | 225/60R16 | 225        | 664.4               | 76.5             |

\* Measured on the tire tread pattern in Shore A.



**Figure 20:** 42 tires tested, 2 vehicles used, and OBSI system with optical sensor implemented for the U.S. Route 460 test.

On the other hand, five tires were tested on the SMART road. Table 10 provides the information of the tires tested. In addition, pictures of the vehicle, OBSI setup and tires tested on the SMART road are shown in Figure 21.

| Table 10: SMART road test tires information |            |           |            |                     |                  |
|---------------------------------------------|------------|-----------|------------|---------------------|------------------|
| Tire number                                 | Condition  | Size      | Width (mm) | Outer diameter (mm) | Rubber hardness* |
| 01                                          | All-season | 215/60R16 | 215        | 664.4               | 73               |
| 09                                          | Winter     | 215/60R16 | 215        | 664.4               | 63               |
| 20                                          | SRTT       | 225/60R16 | 225        | 676.4               | 72               |
| 22                                          | All-season | 225/60R16 | 225        | 676.4               | 75               |
| 24                                          | Winter     | 215/60R16 | 215        | 664.4               | 65               |

\* Measured on the tire tread pattern in Shore A.

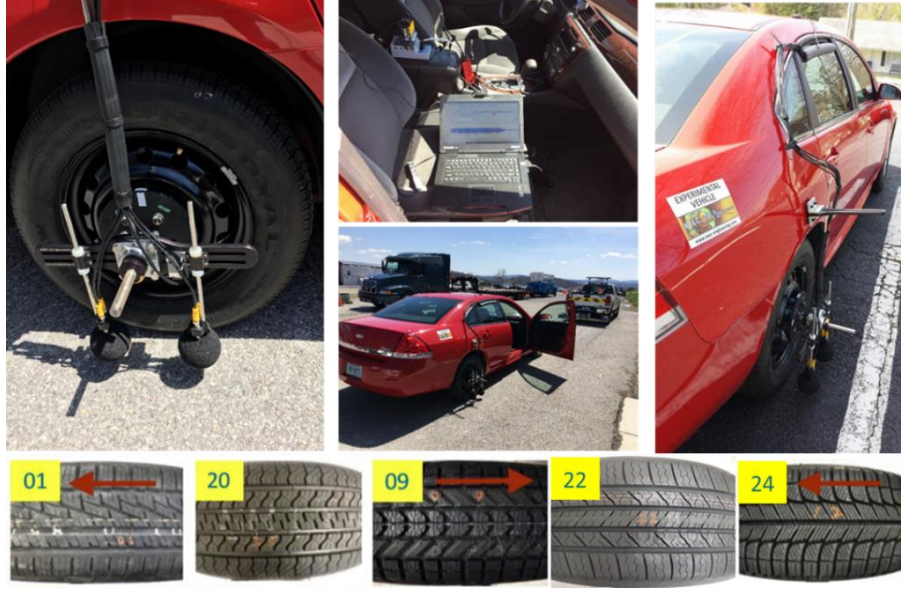


**Figure 21:** Pictures of the OBSI setup and tread pattern of the tires tested on the SMART road.

### 3.3 Experimental results

This section shows both pavement and tire noise data processed results. The dataset includes tire noise for 42 tires and 24 pavements (including the U.S Route 460). The results are used later in this thesis to investigate any possible correlations between the tire noise and the pavement profile data.

#### 3.3.1 *Pavement data*

Figure 22 shows the road pavement profile data acquired by the SCRIM truck on the U.S. Route 460. The start and end point of the tire noise testing section are highlighted. Additionally, a 50 cm example window of the pavement profile is shown.

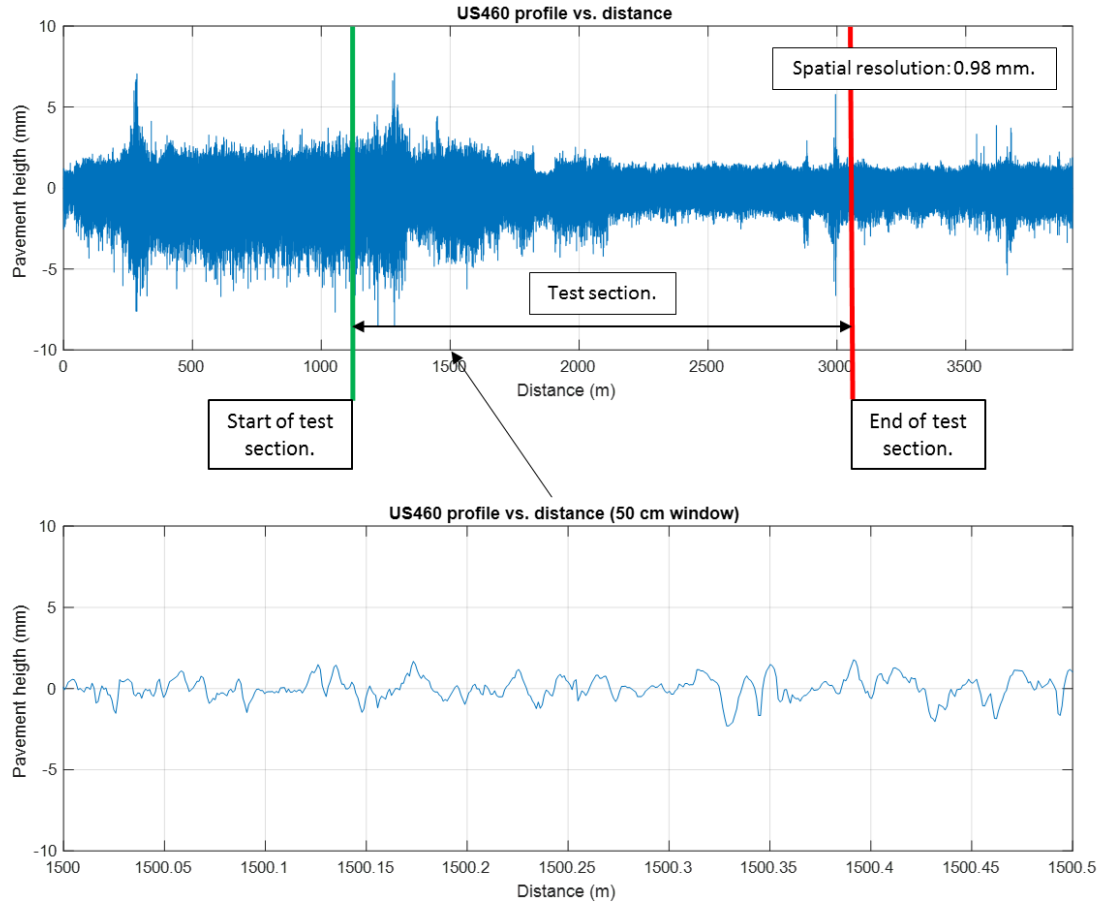


**Figure 22:** U.S. Route 460 road pavement profile. Complete length (top) and 50 cm example window (bottom).

In order to study the effects of the pavement profile on TPIN, the following pavement profile spectrums are computed:

- The wavenumber spectrum.
- The wavelength spectrum.
- The frequency spectrum.

Unlike the frequency spectrum, the wavelength and wavenumber spectrums are independent of the vehicle speed. Since the main interest in this work is to relate pavement profile with tire noise at different vehicle speeds, the pavement profile frequency spectrums are computed for the same discrete vehicle speeds at which the tire noise was collected.

The pavement profile spectrums are computed using the following steps:

- a- Obtain the spatial resolution of the pavement profile data,  $d_{\text{samp}}$ .

- b- Compute the sampling wavenumber  $k_{smp}$  as the inverse of the spatial resolution  $d_{smp}$  multiplied by  $2\pi$ . Its units are [rad/m].
- c- Compute the Nyquist wavenumber  $k_{nyq}$  as half of the sampling wavenumber  $k_{smp}$ .
- d- Compute the sampling time  $T_{smp}$  in terms of the vehicle speed, as

$$T_{smp} = \frac{d_{smp}}{V_{speed}} \quad (3.1)$$

Where  $d_{smp}$  is measured in meters,  $V_{speed}$  in m/s and, therefore  $T_{smp}$  results in seconds.

- e- Divide the data into windows with  $Np$  number of points in each window.
- f- The frequency and wavenumber resolution are denoted as  $f_{res}$  and  $k_{res}$ , respectively. They are computed as

$$f_{res} = \frac{f_{smp}}{Np} \quad (3.2)$$

$$k_{res} = \frac{k_{smp}}{Np} \quad (3.3)$$

- g- Using the frequency and wavenumber resolutions, the frequency and wavenumber vectors are defined as follows:

$$f_{vec} = \{0, f_{res}, 2f_{res}, 3f_{res}, \dots, f_{nyq}\}^T \quad (3.4)$$

$$k_{vec} = \{0, k_{res}, 2k_{res}, 3k_{res}, \dots, k_{nyq}\}^T \quad (3.5)$$

- h- The  $i^{th}$  element of the wavelength vector ( $\lambda_{vec}$ ) in meters is obtained as

$$\lambda_{vec}(i) = \frac{V_{speed}}{f_{vec}(i)} \quad (3.6)$$

- i- The number of windows used to average the spectrums is obtained by dividing the total amount of data points by the number of points  $Np$  inside each window.
- j- Finally, the Discrete Fourier Transform of each window is computed.
- k- The spectrums computed for the windows are incoherently averaged to obtain the final pavement profile spectrum. The spectrum is computed in both linear scale (i.e.,  $\text{mm}^2$ ) and decibel scale with a reference value of  $1\mu\text{m}$
- l- Finally, the pavement wavelength spectrum is plotted in one-third octave bands.

Table 11 shows the values of the parameters to compute the U.S. Route 460 road pavement profile spectrums for different vehicle speeds.

| Table 11: U.S. Route 460 road spectrum parameters (spatial resolution $d_{samp} = 0.98\text{mm}$ ) |          |          |          |          |
|----------------------------------------------------------------------------------------------------|----------|----------|----------|----------|
| Speed [mph]                                                                                        | 45       | 50       | 55       | 60       |
| Sampling time $T_{samp}$ [ $\mu\text{s}$ ]                                                         | 49.00    | 44.10    | 40.09    | 36.75    |
| Sampling frequency $f_{samp}$ [Hz]                                                                 | 20408.16 | 22675.74 | 24943.31 | 27210.88 |
| Nyquist frequency $f_{Nyq}$ [Hz]                                                                   | 10204.08 | 11337.87 | 12471.65 | 13605.44 |
| Number of points $Np$ [-]                                                                          | 4096     | 4096     | 4096     | 4096     |
| Frequency resolution $f_{res}$ [Hz]                                                                | 4.98     | 5.54     | 6.09     | 6.64     |
| Wavenumber resolution $k_{res}$ [rad/m]                                                            | 1.56     | 1.56     | 1.56     | 1.56     |

Table 11 shows that for a spatial resolution  $d_{samp}$  of 0.98 mm, the smaller Nyquist frequency is 10204.08 Hz for a vehicle speed of 45 mph. It is reported in the open literature that the dominant TPIN frequencies are between 600 – 1200 Hz. Therefore, the spatial resolution of the pavement data is excellent for this study. Figure 23 shows the spectrums computed for the U.S. Route 460 road pavement profile. In addition, the figure highlights the relationship between the spectrums.

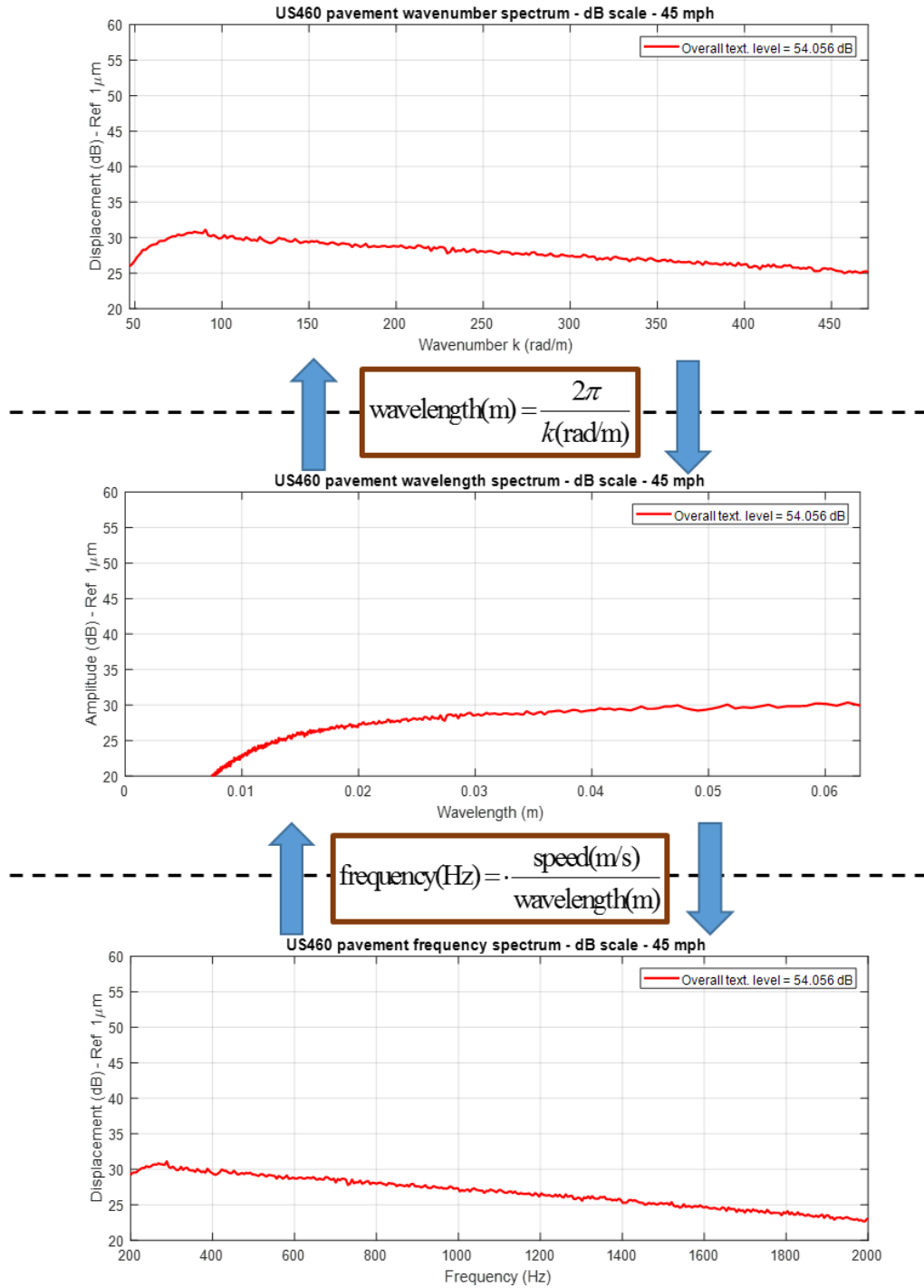


**Figure 23:** US460 road wavenumber (top), wavelength (middle) and frequency (bottom) pavement profile spectra for a vehicle speed of 45 mph.

The pavement profile wavenumber spectrums were also computed for the SMART road surfaces. The spectrums for the pavements with NO transversal grooves are shown in Figure 24. They show a similar shape to the one computed from U.S. Route 460 road data

(see Figure 23). However, there are clear differences on the spectral levels. Most noticeable, for a wavenumber of 100 rad/m, there is approximately a 10 dB difference between the highest and lowest spectral value. This indicates a clear variation on the pavement surfaces texture levels. On the other hand, the spectrums for the pavement sections with transversal grooves are shown in Figure 25. They show the presence of clear tones on their spectrum. It can be observed that the tones occur all at the same wavenumber values, suggesting that the distance between transversal grooves for these sections is the same.

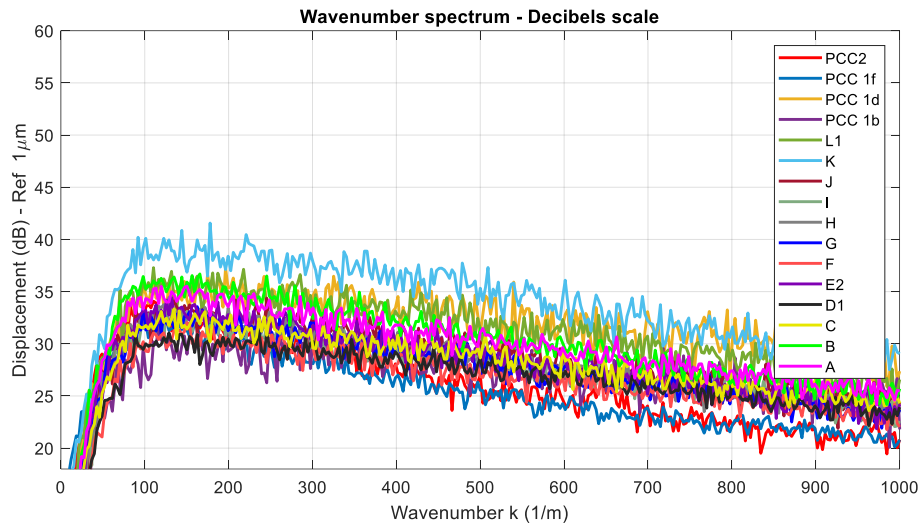


**Figure 24:** Pavement profile wavenumber spectrums of SMART road sections without transversal grooves.

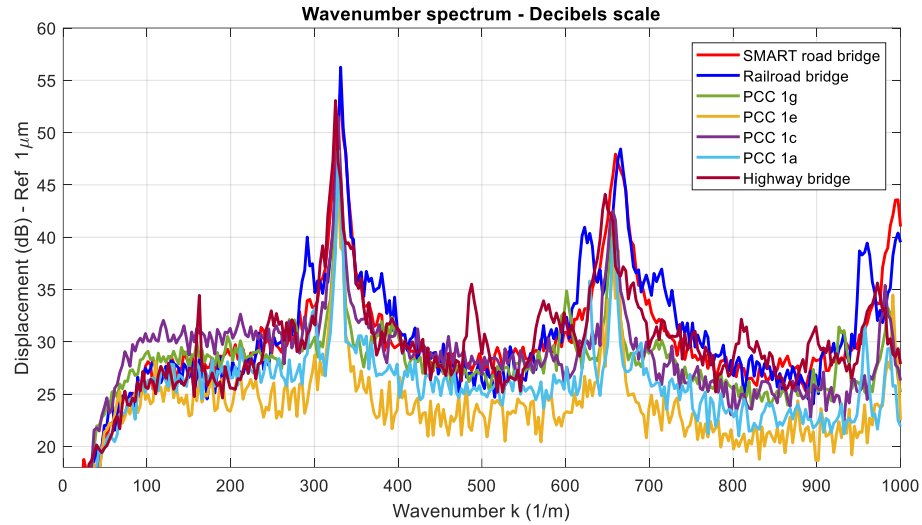


**Figure 25:** Pavement profile spectrums of SMART road sections with transversal grooves.

A frequency spectrogram of the pavement profile data for the entire uphill direction of the SMART road was computed, as shown in Figure 26. The frequency on the vertical axis is calculated using a vehicle speed of 60 mph. On the other hand, the horizontal axis shows the beginning of each pavement section. The spectrogram shows the presence of clear tones at certain pavement sections. They correspond to the same sections with transversal grooves for which the wavenumber spectrum was computed and shown in Figure 25.

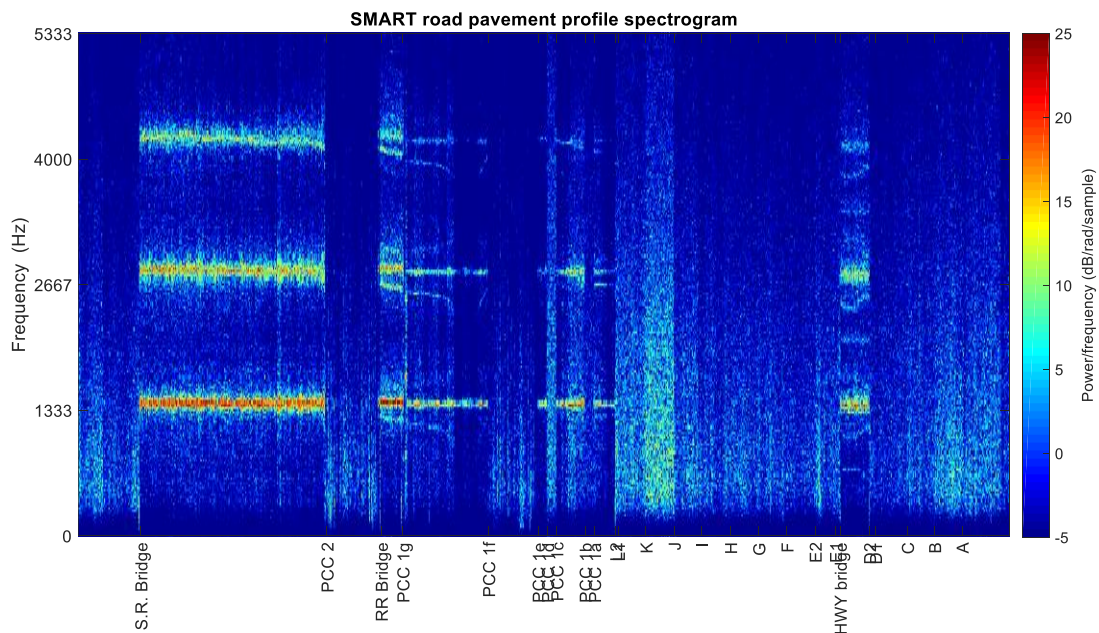


**Figure 26:** SMART road pavement profile spectrogram.

### 3.3.2 Tire noise data

The acquired tire noise data was divided into the TPN and NTPN components. The spectrums and spectrograms were computed for the TTN and the TPN and NTPN components. Figure 27 shows an example of the TTN spectrogram computed for one of the winter tires tested on the SMART road at 60 mph. The observed dominant tire noise frequency range is around 800~1200 Hz (highlighted on the plot). This range matches with what is found in the literature (Sandberg, 2001). Additionally, the presence of clear tones for certain pavement sections can be noticed on the spectrogram.

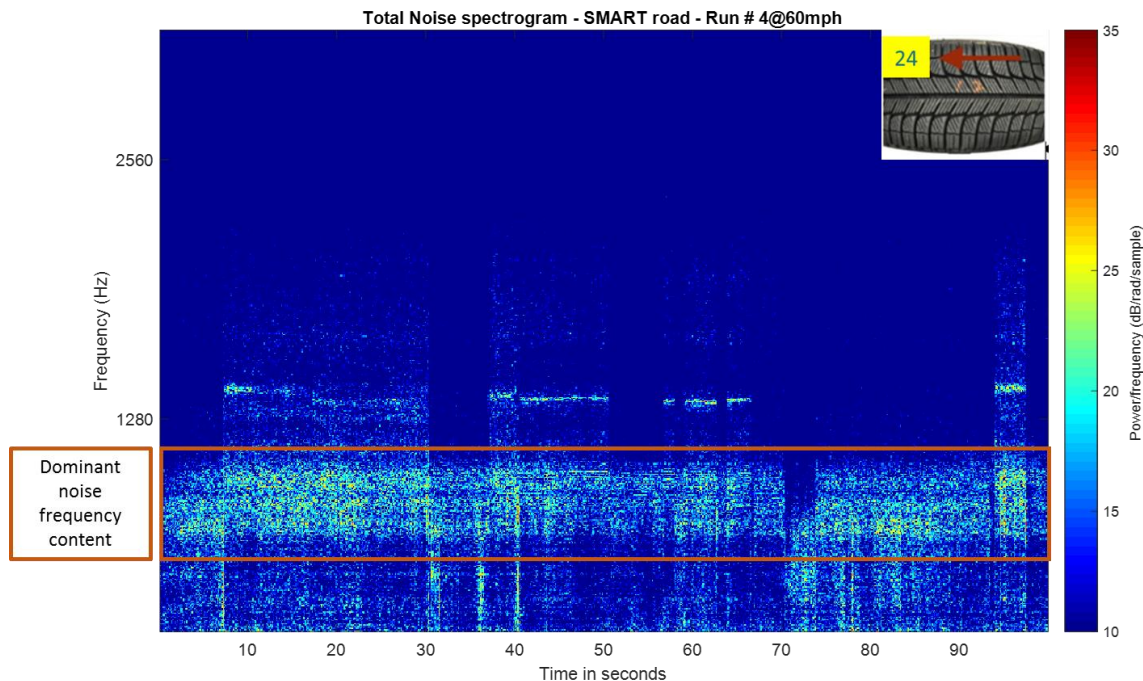


**Figure 27:** SMART road total tire noise spectrogram – Tire 24 – 60 mph.

The next step is to identify the different pavement sections on the tire noise data. This procedure is explained in detail in Appendix C. In the spectrogram presented in Figure 27 there is no tire noise data for sections after the Highway Bridge (i.e., sections A through D). The process to divide the tire noise into the different pavement sections was applied to all the tire noise data collected on the SMART road. Examples of the computed tire noise spectrums (TPN and NTPN) are shown in Figure 28 for 4 types of pavements (dense graded

pavement, OGFC, concrete pavement, and concrete pavement with transversal grooves). In addition, pictures of the pavement surfaces are shown.

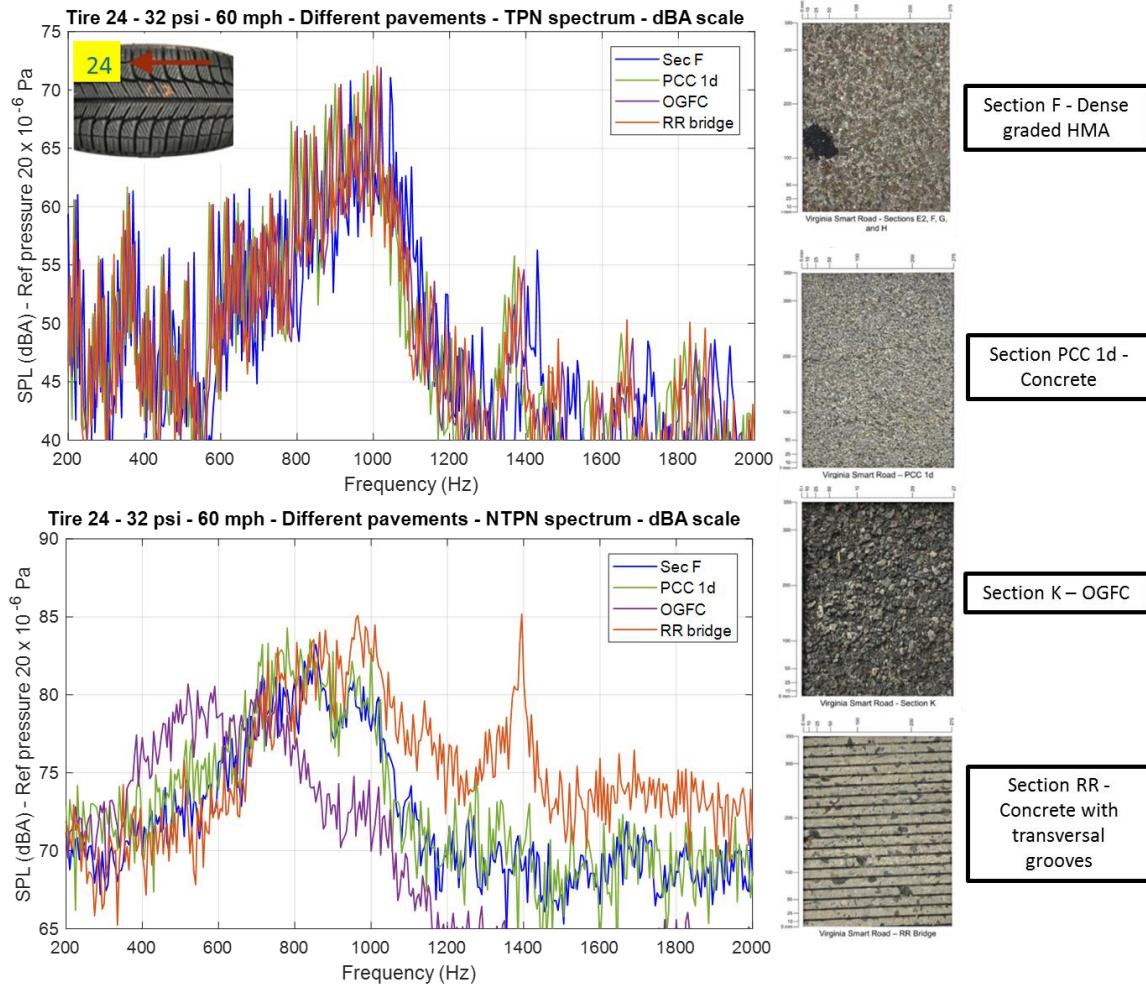


**Figure 28:** TPN and NTPN spectrums for different SMART road pavement sections. Noise data for tire 24 tested at 60 mph. Frequency resolution: 5 Hz.

### 3.4 Pavement profile and tire noise relationship

TPIN behavior for different road surfaces was investigated by analyzing both tire noise and pavement data. The TPN and NTPN relationship with the pavement surface are discussed separately in this section. As an illustration of the separation of the TPN and NTPN components, Figure 28 shows an example of both independent components narrowband spectrums obtained in decibel scale for different pavements. The frequency resolution for such plot is 5 Hz. Comparing multiple noise spectrums for several pavements would not be very clear. Therefore, in this section the spectrum is computed using an intermediate narrowband frequency of 20 Hz.

Within the NTPN study, the pavements with and without grooves are studied independently. Finally, the conclusions of this study are presented.

#### *3.4.1 TPN independency from pavement profile*

Figure 29 shows the comparison of the TPN spectrums for different pavement sections for Tire 24, using a pressure of 32 psi and a vehicle speed of 60 mph. Continuous lines represent asphalt pavements, while dashed lines represent concrete pavement surfaces (bridges are included in this category). It becomes clear from the figure that the TPN for all the different studied pavement surfaces is very similar. The spectrogram for the same tire and testing conditions is computed and shown in Figure 30.

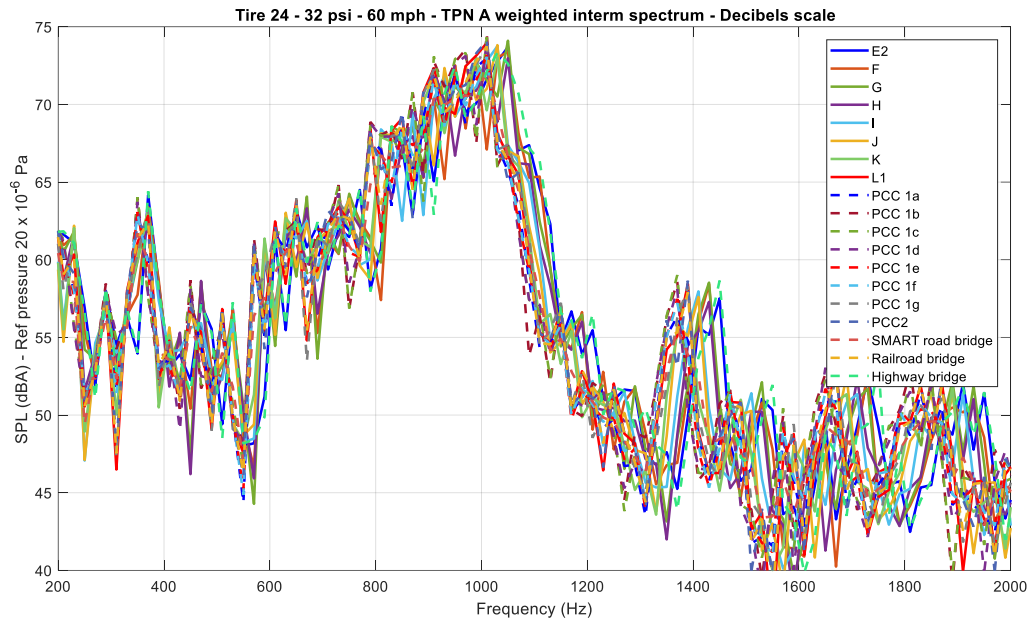


**Figure 29:** TPN spectrum comparison for the different pavements on the SMART road. Tire 24 – 32 psi – 60 mph. Continuous line: Asphalts, Dashed line: Concrete pavements. Frequency resolution: 20 Hz.

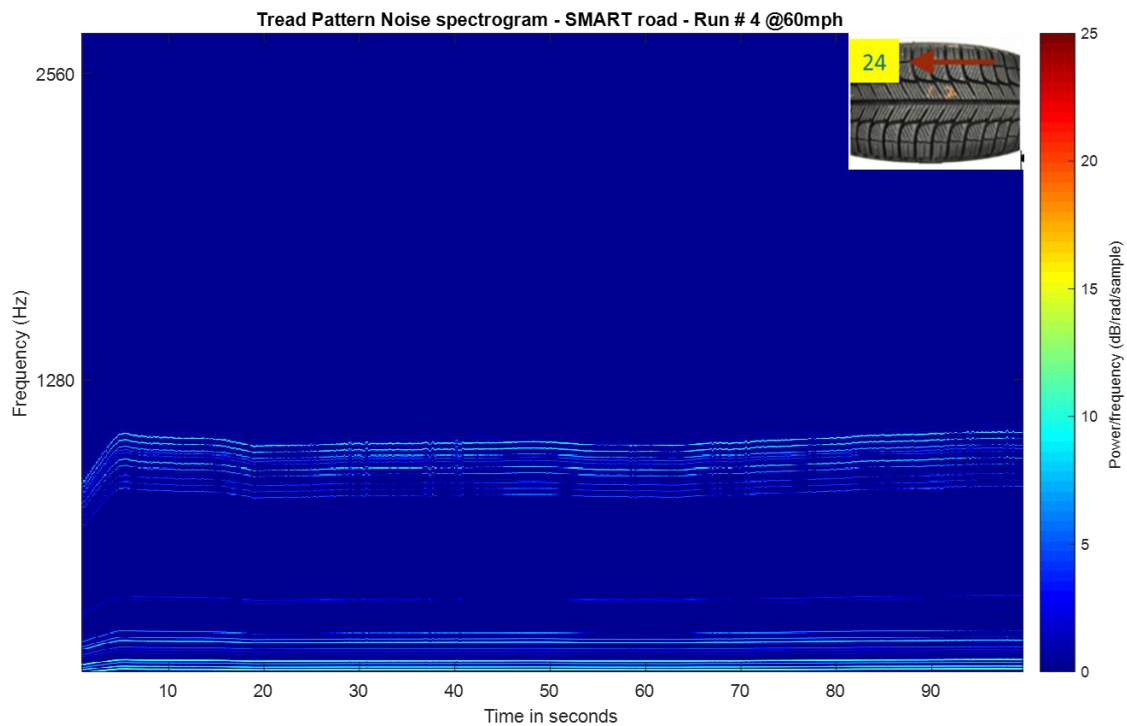


**Figure 30:** SMART road TPN spectrogram – Tire 24 – 60 mph.

In the spectrogram presented in Figure 30 it is clear that the TPN component remains the same along the entire SMART road test. Therefore, Figure 29 and Figure 30 provide strong evidence to support that the TPN component of tire noise is independent from the pavement surface texture.

### 3.4.2 NTPN dependency from pavement profile

The same analysis performed for the TPN in the previous subsection was conducted for the NTPN component of tire noise (same tire, pressure and vehicle speed). Figure 31 shows the same comparison made on Figure 30, but the NTPN spectrums are compared this time. It becomes clear from the figure that NTPN varies considerably from one pavement surface to another (the complete opposite behavior observed for the TPN component). Though the spectral shape for different pavements remains about the same (a clear exemption is pavement K), the levels varies considerable from pavement to pavement.

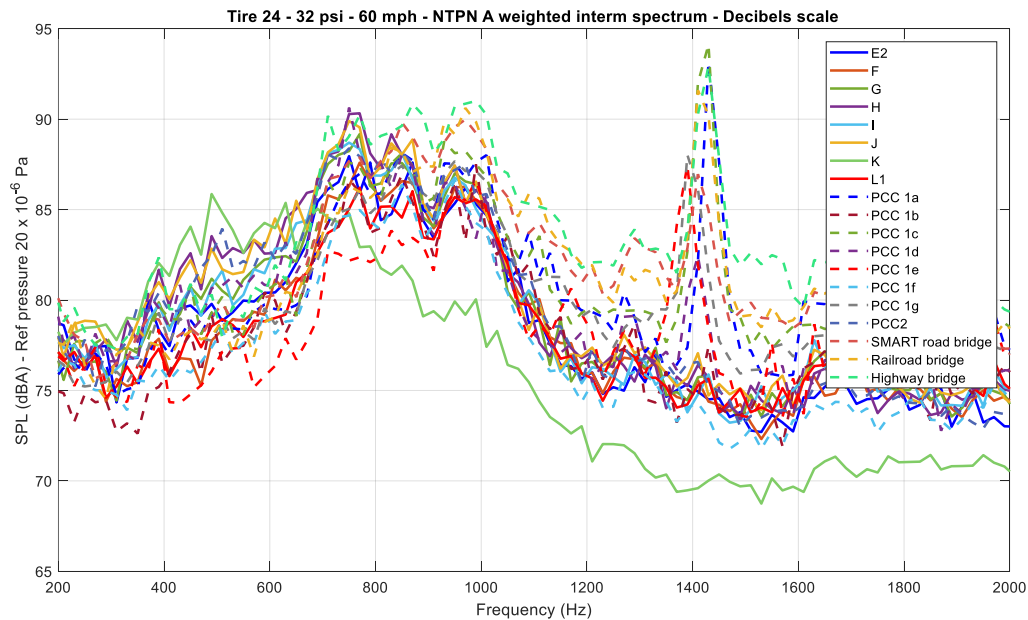


**Figure 31:** NTPN spectrum comparison for the different pavements on the SMART road. Tire 24 – 32 psi – 60 mph. Continuous line: Asphalts, Dashed line: Concrete pavements. Frequency resolution: 20 Hz.

Additionally, the NTPN spectrogram was computed as shown in Figure 32. Both figures show the presence of clear tones (around 1400 Hz for a vehicle speed of 60 mph) at certain pavement sections on the SMART road. These tones are due to the presence of transversal grooves on the pavement surface. These pavement sections are highlighted in the NTPN spectrogram shown in Figure 32. In addition, pictures of the pavement surfaces corresponding to each section are shown.

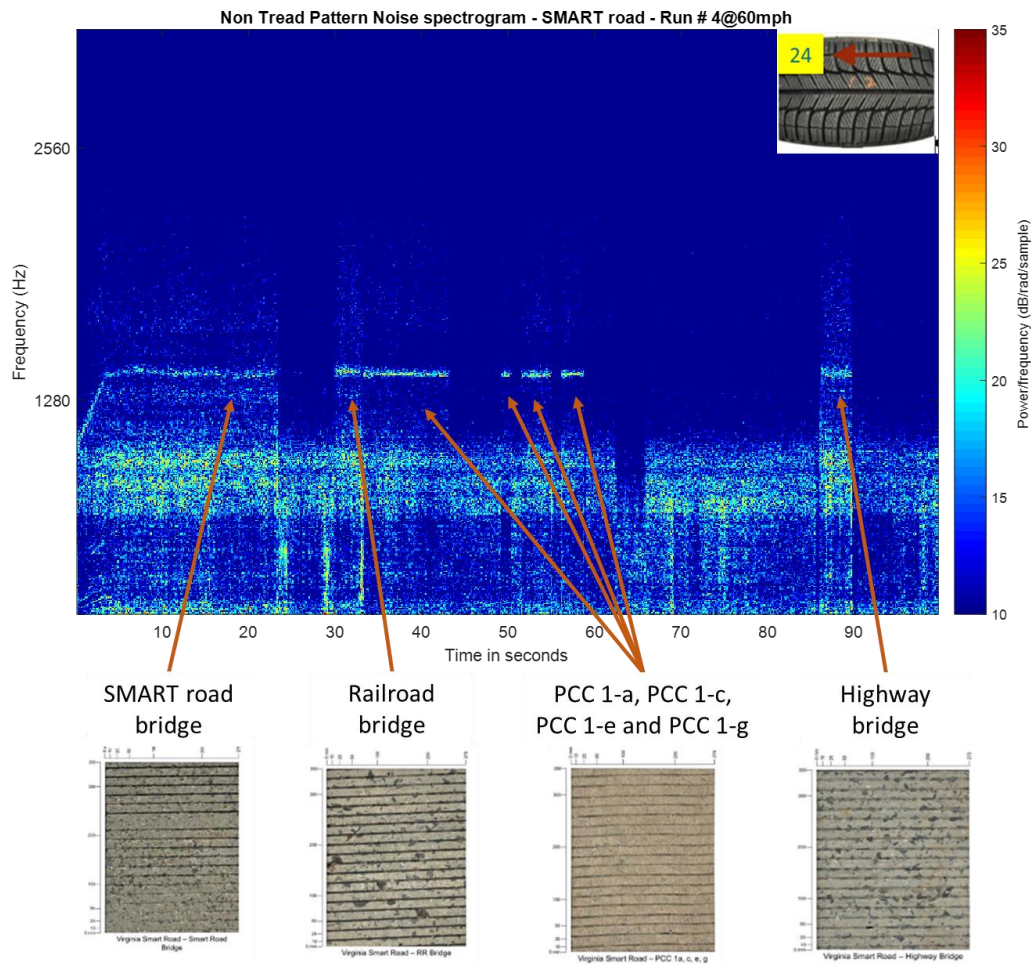


**Figure 32:** SMART road NTPN spectrogram – Tire 24 – 60 mph. Pavement with presence of transversal grooves highlighted.

In order to explain the relationship found between the tire noise and pavement data corresponding to pavements with transversal grooves, the pavement profile spectrum and NTPN spectrum for the section PCC-1c are computed and compared in Figure 33.

It is possible to estimate the pavement profile transversal groove wavelength ( $\lambda_{grooves}$ ) from the NTPN spectrum using Equation 3.8. In fact:

$$\lambda_{grooves} = \frac{f_{rot-tire} \cdot l_{tire}}{f_{tone}} = \frac{12.8Hz \cdot 2.08m}{1400Hz} \cong 0.0192m \quad (3.8)$$

In Equation 3.8,  $f_{rot-tire}$  denotes the tire rotation frequency in Hz (in this case for a vehicle speed of 60 mph),  $l_{tire}$  represents the length of the circumference of the tire in meters, and  $f_{tone}$  is the frequency of the NTPN tone in Hz

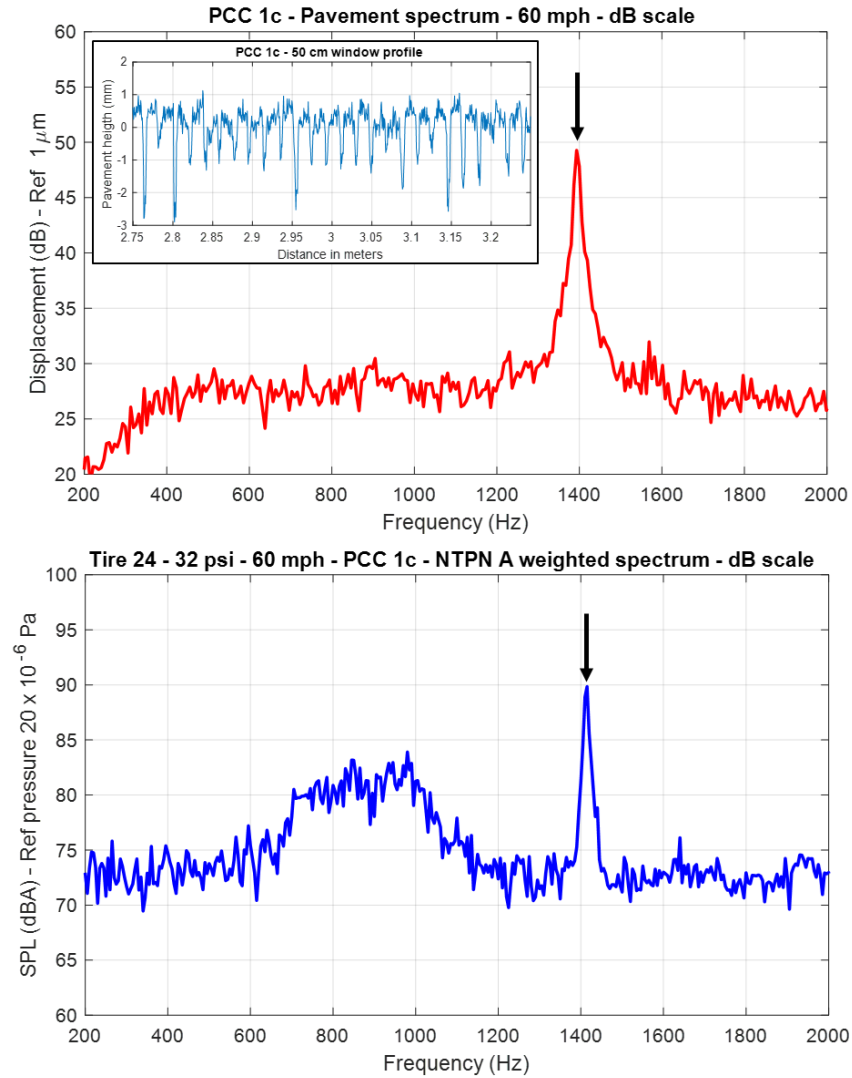


**Figure 33:** SMART road section PCC-1c pavement profile example and frequency spectrum at 60 mph. Frequency resolution: 6.5 Hz (top). NTPN spectrum for tire 24. Frequency resolution: 5 Hz (bottom).

In addition, using the transformation shown in Figure 23, the pavement profile wavelength spectrum is computed from the pavement profile data and presented in Figure 34. The wavelength computed using Equation 3.8 (i.e., the tone frequency observed on the NTPN spectrum) and the one obtained from the pavement profile data match very well.

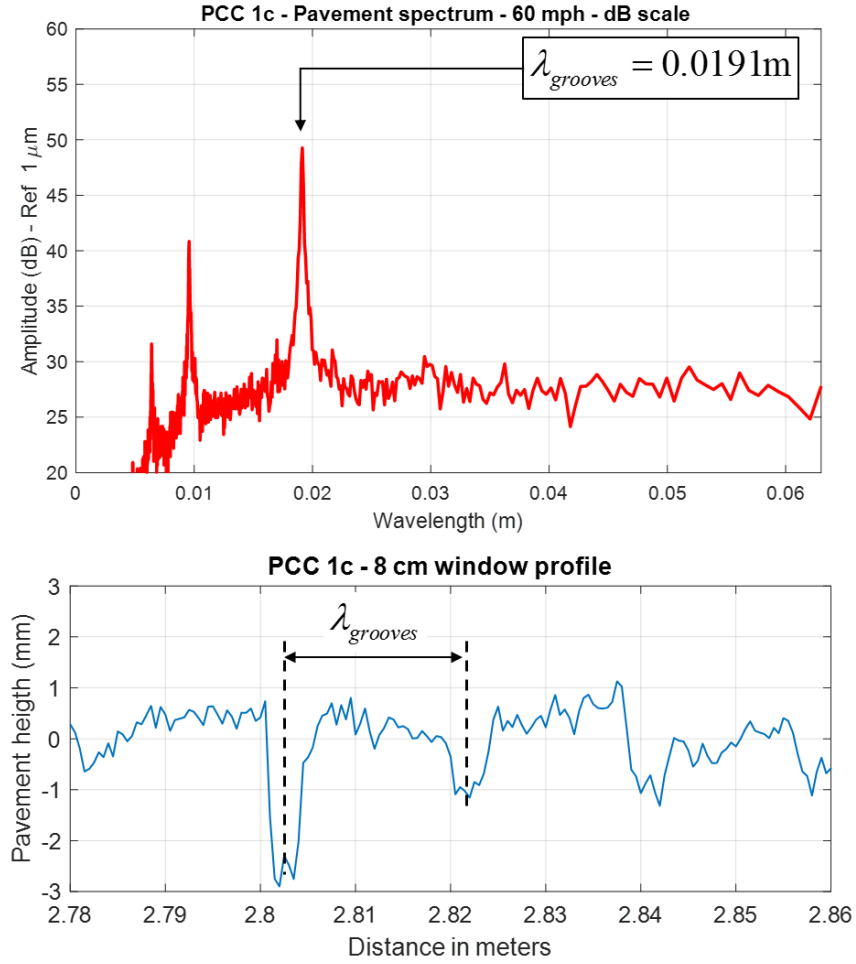


**Figure 34:** SMART road section PCC-1c pavement profile wavelength spectrum (top). SMART road section PCC-1c pavement profile 8 cm example window (bottom).

The inverse process is explained using the same pavement profile. However, instead of 60 mph, the NTPN spectrum for a vehicle speed of 45 mph is used ( $f_{rot-tire} = 9.6\text{Hz}$ ). Using Equation 3.9, it is possible to estimate the frequency at which the tone should be seen in the NTPN spectrum. In fact:

$$f_{tone} = \frac{f_{rot-tire} \cdot l_{tire}}{\lambda_{grooves}} = \frac{9.6\text{Hz} \cdot 2.08\text{m}}{0.0192\text{m}} \cong 1040\text{Hz} \quad (3.9)$$

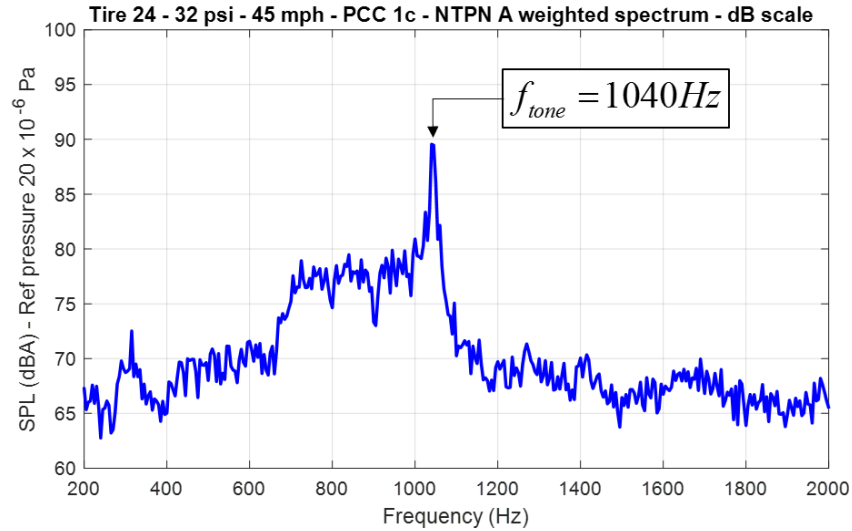


**Figure 35:** SMART road section PCC-1c NTPN spectrum for tire 24 at 45 mph. Frequency resolution: 5 Hz (bottom).

It can be concluded that for pavement surfaces with transversal grooves, a very good estimation of the grooves wavelength can be made using:

- the NTPN spectrum data (frequency where the tone occurs),
- the tire information (outer diameter), and
- the driving conditions at which the noise was collected (vehicle speed).

In the case of the non-porous pavements, the relationship between the NTPN and the pavement profile will be study using three non-porous pavements. They are:

- Section F, which is a dense graded mix with a maximum aggregate size of 9.5 mm (SM-9.5)
- Section I, which is also a dense graded mix with a maximum aggregate size of 9.5 mm. (SM-9.5). The only difference with respect to section F is the binder.
- Section PCC-1d, which is a non-porous concrete pavement surface.

Figure 36 shows the NTPN spectrums and the pavement profile frequency spectrums for the SRTT tire tested at 55 mph on the three pavement sections specified above. In addition, pictures show the pavement surface of each section.

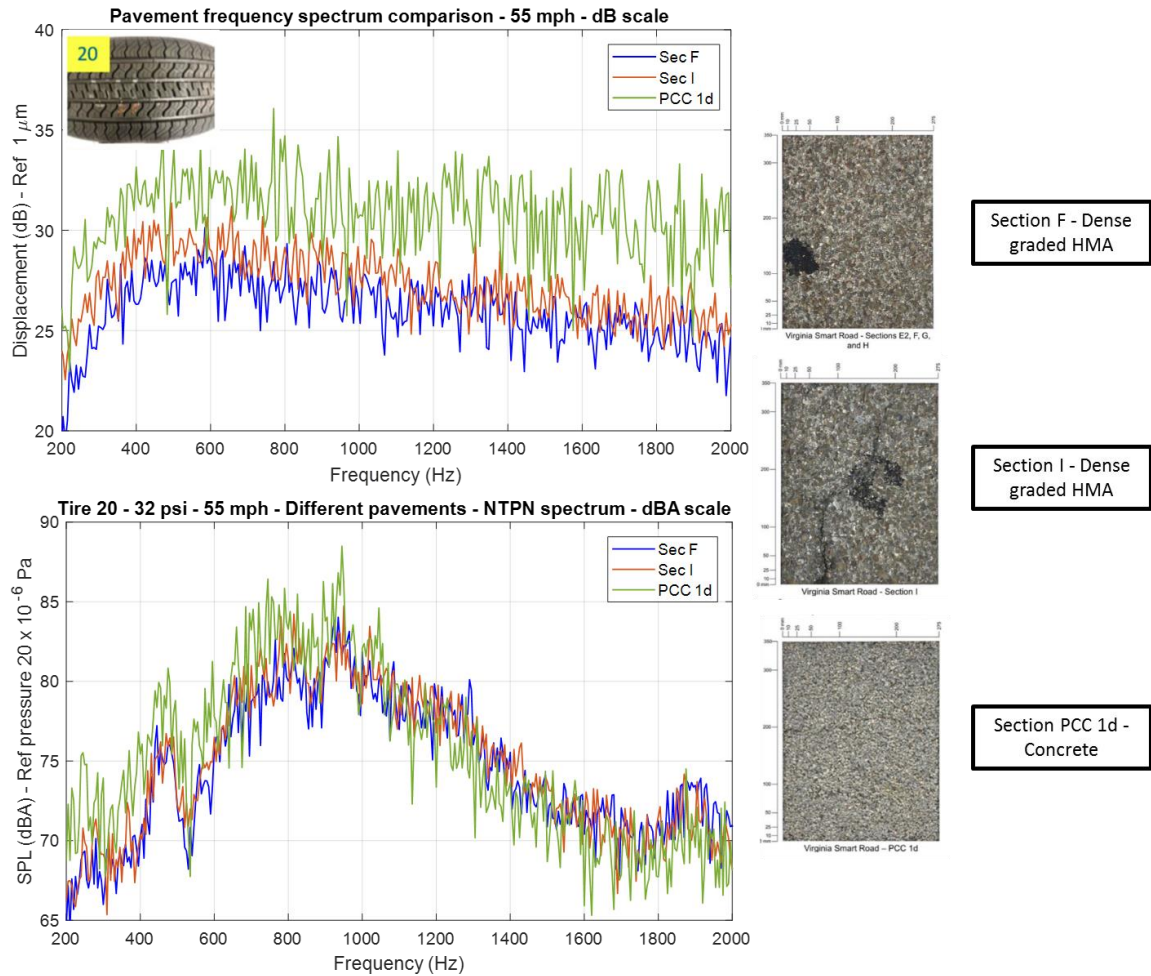


**Figure 36:** SMART road sections F, I and PCC-1d pavement frequency spectrums at 55 mph. Frequency resolution: 6.5 Hz (top-left). NTPN spectrums for tire 20 (SRTT) at 55 mph. Frequency resolution: 5 Hz (bottom).

The pavement profile spectrums presented in Figure 36 have a similar shape (also observed in Figure 24). However, there is a clear difference on the texture levels for each pavement section. The concrete section (i.e., PCC-1d) shows higher texture levels than the two hot mix asphalt surfaces. Section I shows a slightly higher texture level than section F. Analyzing the NTPN plot for the same pavement sections two main observations can be made:

- Firstly, at the low frequencies of the NTPN spectrum (i.e., frequencies below 1000 Hz), the pavement section with the higher texture level (i.e., section PCC-1d) shows a clear increase on the noise levels if compared with the other two pavement sections (i.e., sections F and I). This behavior is consistent with what has been reported in the

literature (Sandberg et al., 1980). Pavement surfaces with high texture levels are speculated to be related to higher radial excitation of the tire. Hence, an increase on the noise levels at low frequencies.

- Secondly, an opposite behavior is observed at the higher frequencies of the NTPN spectrum (i.e., frequencies above 1000 Hz). The pavement surface with a higher texture level on the pavement profile spectrum (i.e., PCC-1d) shows lower noise levels when compared with the dense graded mixes (i.e., sections F and I). In this case, the increase on the texture levels of the pavement at high frequencies can be associated to a decrease of the air pumping noise generation mechanism. High texture levels and thus larger cavities in the pavement provide the means to reduce the compression of the air between the tire and the pavement surface.

A similar trend is observed between the NTPN and pavement profile spectrums for the dense graded mixes. However, these observations are not as evident as when comparing the two dense graded mixes (sections F and I) with the concrete section (section PCC-1d). It is important to highlight that the observations previously made on the NTPN and pavement data follows what has been reported in the literature. Sandberg (1987) reported both positive and negative correlations between tire noise and pavement texture levels. He also reported that the frequency where the correlation between tire noise and pavement texture changes from a positive to a negative relationship is approximately 1000 - 1250 Hz for passenger car tires, and called it *crossover frequency*. The main difference between his analysis and the one presented in this chapter is that he related pavement texture wavelength with tire noise at a fixed vehicle speed (i.e., 80 km/h), while our observations are made at different vehicle speeds and pavement texture frequency spectrums are used instead.

Although the results are presented for the SRTT tire at one single speed, a similar behavior was observed for all the tires tested on the SMART road at the different speeds tested.

The SMART road offers several non-porous pavement surfaces. However, there is only one porous pavement surface (i.e., section K corresponds to an Open Graded Friction Course). Figure 37 adds the porous pavement surface data to the previous analysis.

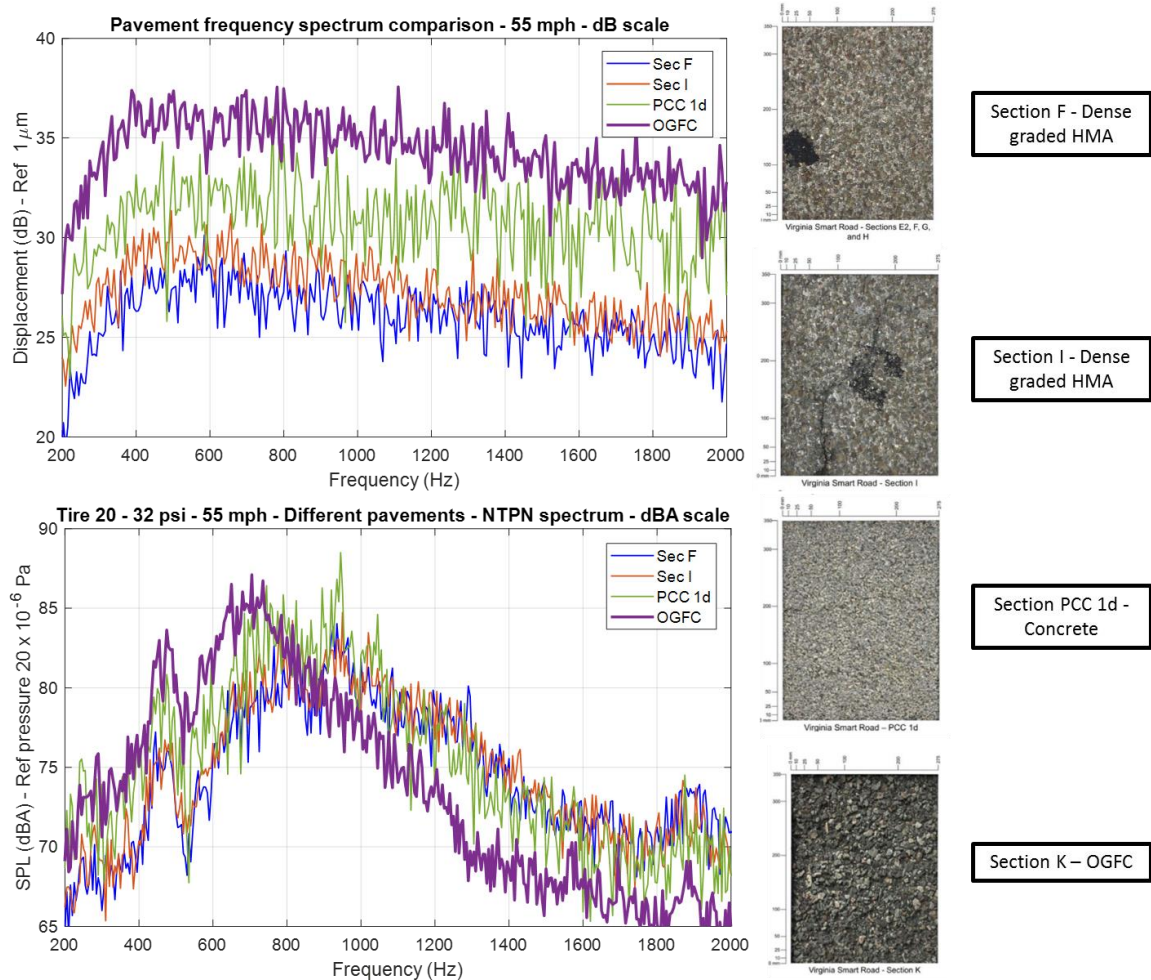


**Figure 37:** SMART road sections F, I, PCC-1d and K pavement frequency spectrums at 55 mph. Frequency resolution: 6.5 Hz (top-left). NTPN spectrums for tire 20 (SRTT) at 55 mph. Frequency resolution: 5 Hz (bottom).

The same behavior at low and high frequencies of the NTPN is observed. The significant increase on the texture level for the OGFC significantly increases the noise at low frequency (likely tire vibration). On the other hand, the noise levels at high frequencies for the OGFC are substantially lower when compared with the lower texture surfaces. The same conclusions made on the previous case apply to this analysis. However, the decrease of tire noise at higher frequencies for the OGFC is much higher than the one observed

between the non-porous pavements sections. Such decrease on the noise levels can be attributed to a second noise reduction mechanism. The presence of interconnected air voids in the OGFC surface provide a mechanism for dissipating the acoustic energy of the air pumping as shown in Figure 38 (R. J. Bernhard et al., 2005).

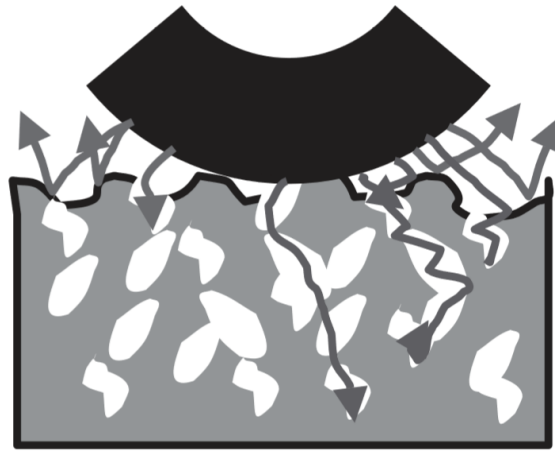


**Figure 38:** Porous pavement effect on tire noise (R. J. Bernhard et al., 2005).

Figure 39 shows the comparison of a 50 cm window between the OGFC and the non-porous pavement section F. The size of the cavities between the tire and the pavement surface are much larger for the OGFC pavement. Large cavities will decrease the buildup pressure between the tire and the pavement surface, hence, a decrease on the noise due to air pumping is expected. Unfortunately, results for a single porous pavement does not provide enough information to determine its relationship with TPIN.

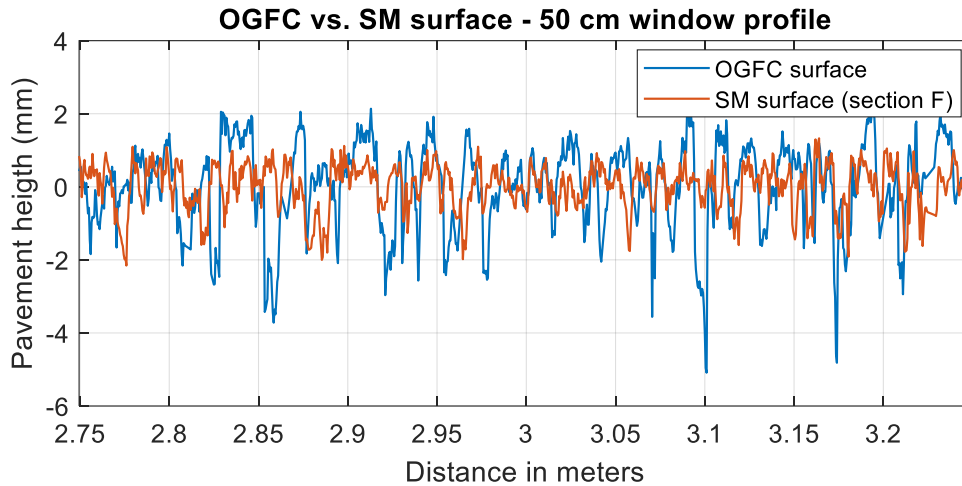


**Figure 39:** 50 cm window comparing a regular surface mix (SM) pavement profile with the open graded friction course (OGFC) pavement profile.

For this study, the sound absorption coefficients for the different pavements tested was not measured. However, if a deeper understanding of how tire noise behaves in porous pavement surfaces is desired, the measurement of sound absorption coefficients should be carried out. This is outside the scope of this thesis.

### 3.4.3 Conclusions

Using all the experimental results corresponding to both tire noise and pavement profile data, we can conclude that:

1. The TPN component is independent from the pavement surface (see Figure 29).
2. The NTPN component varies (spectral shape and values) for the different pavement surfaces tested, suggesting that the NTPN component is strongly dependent on the pavement surface parameters (see Figure 31).
3. It is observed that in non-porous pavements surfaces, an increase on the texture levels produces an increase on the NTPN noise levels at low frequencies ( $< 1000$  Hz). On the other hand, the increase in texture levels of non-porous pavement surfaces results in a decrease on the NTPN noise levels at high frequencies ( $> 1000$  Hz).
4. The analysis of the NTPN provides information about specific pavement surface features such as transversal grooves. The wavelength of the pavement surface

features can be estimated using tire noise spectrum, vehicle speed, tire circumference, and frequency at which the tones are observed on the NTPN spectrum.

5. The presence of large air voids in the pavement surface (i.e., porous pavements) creates a significant decrease of the noise levels at high frequencies while it increases the tire noise a low frequencies.

The analysis carried out in this chapter clearly indicates that the NTPN component is strongly related to the pavement profile features. If the objective is to develop a method to account for pavement parameters when predicting TPIN, the NTPN is the only component that must be adjusted based on the pavement properties.

## 4 Prediction of TPIN for different pavement surfaces

The analysis of the large amount of tire noise and pavement data collected at the SMART road and U.S. Route 460 (presented in the previous chapter) provided strong evidence to support that: I) the TPN is independent on the pavement surface profile and that II) the NTPN component of the tire noise is dependent on the pavement surface features. In his work, Li (2017) took into account only tire parameters when predicting TPIN (presented in Subsection 1.2.3). He did not consider pavement surface parameters. This chapter presents an approach developed in order to incorporate into Li's model the capability of taking into account the pavement surface profile when predicting the NTPN component of tire noise (only component related to the pavement surface). Since there is not enough data to include porous pavements and pavement surfaces with transversal grooves, only non-porous pavements without transversal grooves are considered for the current model development.

First the proposed approach to incorporate the pavement profile information to predict NTPN, which is based on a scaling procedure, is briefly introduced. Moreover, a weighting function to be used in the pavement scaling process is investigated using the available tire noise and pavement profile data. Finally, the NTPN results obtained for different pavement surfaces implementing the proposed approach are presented and discussed.

### 4.1 NTPN prediction approach for non-porous pavements

#### 4.1.1 *Approach description*

The model presented by Li predicts TPIN using only tire parameters as inputs (see Figure 5). In his model, first an ANN predicts the NTPN spectrum for a reference tire size (i.e., 215/60R16) using as inputs the vehicle speed and the tread pattern rubber. The ANN was trained using tire noise data collected at multiple speeds on the U.S. Route 460. Therefore, the ANN will be able to predict the NTPN produced by a tire rolling on a pavement surface with the same profile spectrum as the U.S. Route 460 road. Thus, the

U.S. Route 460 is from now on referred as the “reference pavement”. Finally, the NTPN predicted for the reference tire and the reference pavement surface is then scaled for a different tire size. The scaling procedure is based on a relationship between the reference and input tire carcass width. The final result is the NTPN frequency spectrum for an input vehicle speed, tread pattern rubber hardness, tire size and the reference pavement (U.S. Route 460).

It is proposed to incorporate a new module to Li’s model. Such a module will correct the NTPN predicted for the reference pavement to any arbitrary non-porous pavement profile, referred from now on as the “input pavement”.

The data available to investigate and develop the proposed module includes:

- Tire noise data collected for four different tires on several non-porous pavements highlighted in Figure 40 (presented in Section 3.2).
- Pavement profile data for the same non-porous pavement sections where tire noise was collected. It also includes the pavement profile of the reference pavement surface (U.S. Route 460).

As it was mentioned before, the optical sensor data was corrupted for the test involving Tire 09. Therefore, the NTPN data for this specific tire was not used for validation purposes.

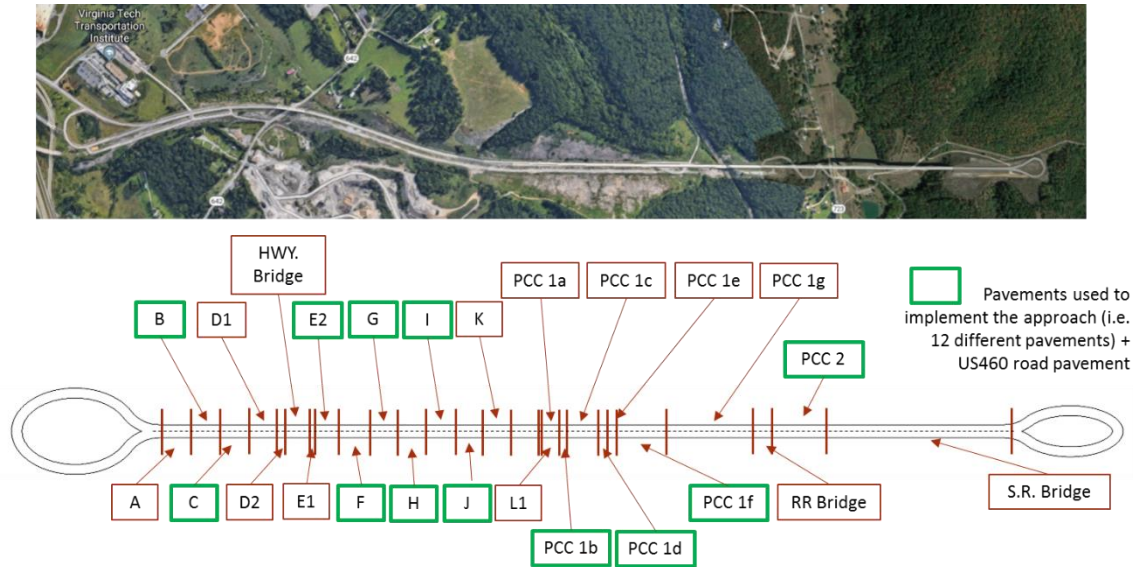


**Figure 40:** SMART road pavements used for the development of the approach.

The tires tested on different pavement surfaces have a similar tire size as the reference tire (215/60R16). Larger tire sizes were not tested on the SMART road. Therefore, the module to predict the NTPN based on the input pavement profile will be implemented prior to the NTPN tire carcass width scaling process. Figure 41 shows a simplified graphical schematic of the new NTPN prediction approach.

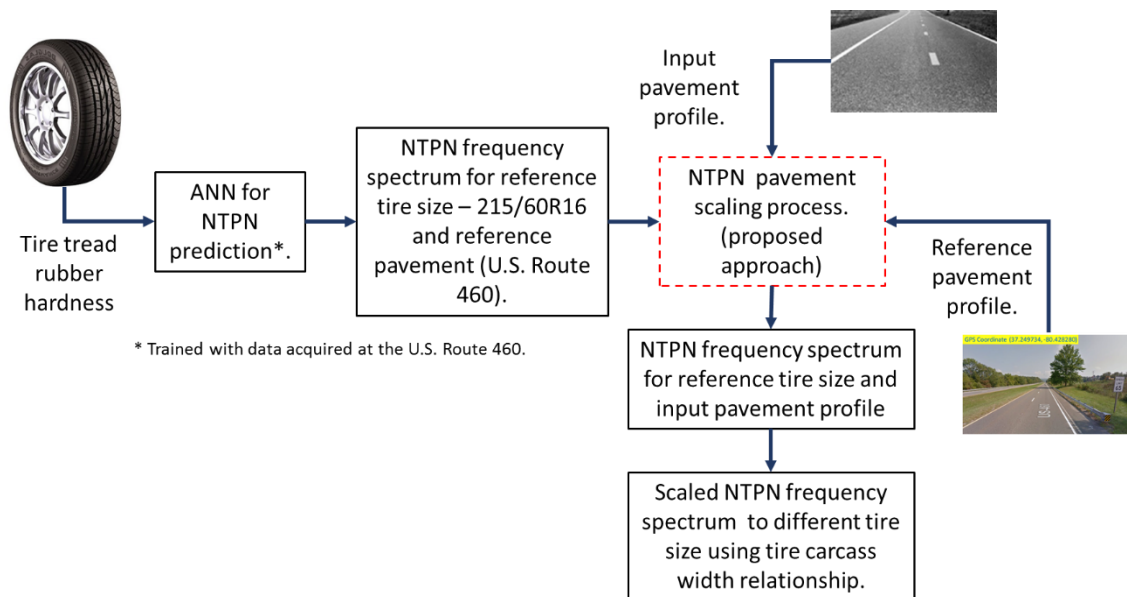


**Figure 41:** Main objective of the proposed approach.

It is proposed to add the “NTPN pavement scaling process” module (dashed red line box in Figure 41) to the NTPN prediction branch of the model presented in Figure 5. Since the proposed approach corrects the NTPN predicted for a reference tire and a reference pavement before the tire carcass width scaling procedure, an implicit assumption is made: the effect of the pavement surface on the NTPN is independent of the size of the tires. The details of the approach formulation are discussed in the following subsection.

#### 4.1.2 NTPN correction based on input pavement profile spectrum

The computation process taking place inside the “NTPN pavement scaling process” module is shown in the schematic presented in Figure 42.

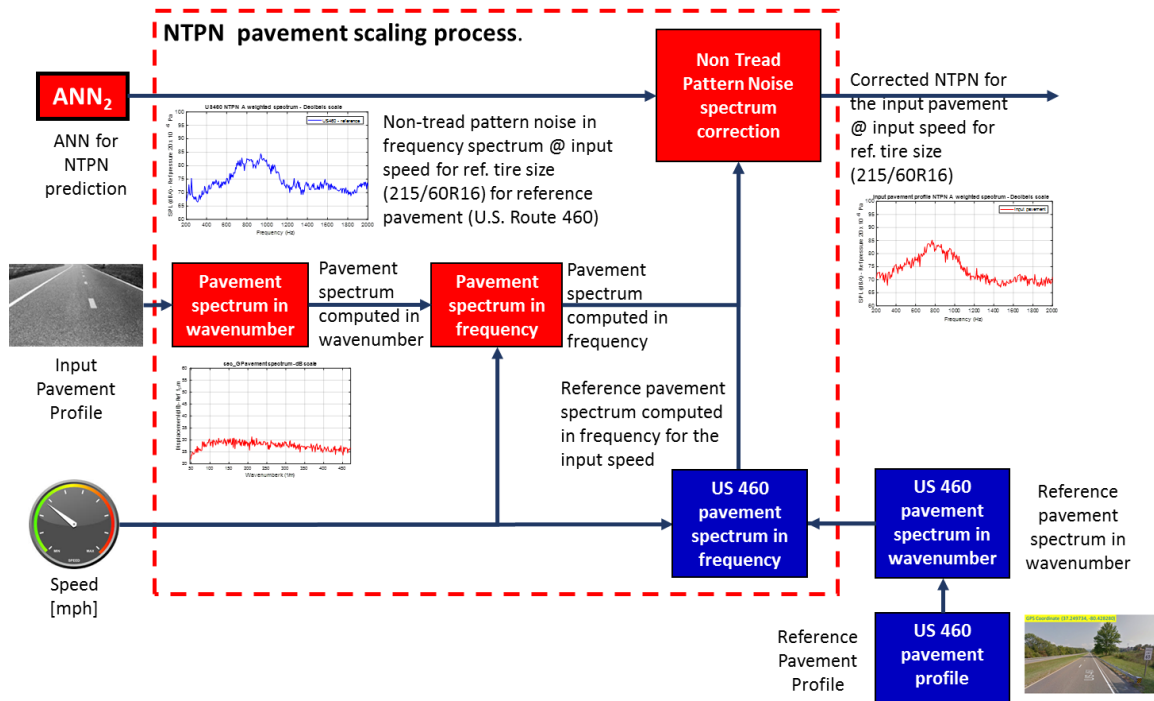


**Figure 42:** NTPN pavement scaling process computation description.

The inputs to such a module are:

- The NTPN predicted by the ANN for the reference tire size (i.e., 215/60R16) and a reference pavement profile (i.e., U.S. Route 460).
- The input non-porous pavement profile for which the NTPN is corrected for.

- The vehicle speed at which the NTPN is predicted (used to convert the pavement wavenumber spectrums to frequency spectrum).
- The reference pavement profile.

A function to correct the NTPN frequency spectrum for the reference pavement to any arbitrary input non-porous pavement profile needs to be defined. Then, the output of the module would be the corrected NTPN for the input pavement profile at the input vehicle speed and the reference tire size. Finally, the NTPN predicted by the module is scaled to any arbitrary tire size using the tire carcass width relationship.

The first step towards the formulation of the required NTPN correcting function is to relate the tire noise frequency spectrum with the pavement profile frequency spectrum for different pavement surfaces. In order to do so, the transfer function magnitude between the NTPN spectrum and the pavement profile spectrum (both with respect to frequency) is computed as follows,

$$TF_{nn/pp} = \frac{S_{nn}}{S_{pp}}, \quad (4.1)$$

where  $S_{nn}$  is the NTPN frequency spectrum and  $S_{pp}$  the pavement profile frequency spectrum. The units of  $TF_{nn/pp}$  are  $Pa^2/m^2$ . In the case of the pavement profile, the wavenumber spectrum is computed in first place. Then, the pavement profile frequency spectrum  $S_{pp}$  is computed following the procedure explained in Subsection 3.3.1. This is done using the vehicle speed at which the NTPN was collected. Moreover, in order to compute the transfer function, the frequency resolution for both spectrums must be the same.

Secondly, the transfer function shown in Equation 4.1 is computed for the reference pavement (*ref – pave*) and for any arbitrary input non-porous pavement profile (i.e., *in – pave*). Thus,

$$TF_{ref-pave} = \frac{S_{nn(ref-pave)}}{S_{pp(ref-pave)}} \quad (4.2)$$

and

$$TF_{in-pave} = \frac{S_{nn(in-pave)}}{S_{pp(in-pave)}} \quad (4.3)$$

where  $S_{nn(ref-pave)}$  and  $S_{nn(in-pave)}$  are the NTPN frequency spectrum computed for the reference pavement (U.S. Route 460) and the input pavement respectively.  $S_{pp(ref-pave)}$  and  $S_{pp(in-pave)}$  are the pavement profile frequency spectrums computed for the reference and input pavement profiles respectively. From Equations 4.2 and 4.3 it follows that:

$$S_{nn(ref-pave)} = TF_{ref-pave} \cdot S_{pp(ref-pave)} \quad (4.4)$$

and

$$S_{nn(in-pave)} = TF_{in-pave} \cdot S_{pp(in-pave)} \quad (4.5)$$

and therefore

$$S_{nn(in-pave)} = S_{nn(ref-pave)} \cdot \frac{S_{pp(in-pave)}}{S_{pp(ref-pave)}} \cdot \frac{TF_{in-pave}}{TF_{ref-pave}} \quad (4.6)$$

From now on, the last factor in Equation 4.6 (i.e., the ratio between the input and the reference transfer functions) will be called the “R function” and will be denoted by  $\bar{R}$ :

$$\bar{R} = \frac{TF_{in-pave}}{TF_{ref-pave}} \quad (4.7)$$

Thus, Equation 4.6 can now be written as:

$$S_{nn(in-pave)} = S_{nn(ref-pave)} \cdot \frac{S_{pp(in-pave)}}{S_{pp(ref-pave)}} \cdot \bar{R} \quad (4.8)$$

The experimental data collected for multiple tires on multiple non-porous pavements will be used to study the behavior of the R function and estimate it.

#### 4.1.3 Weighting function (R-function)

The transfer function in Equation 4.1 is computed using the NTPN for Tire 24 and the non-porous pavement profile spectrums. This is done for the vehicle speeds of 60 and 45 mph. The results are shown in Figure 43 and Figure 44 in decibel scale, where the reference value is 1. The shape of the transfer function for the same vehicle speed on different pavement surfaces look similar within the frequency range of interest (i.e., 400-1600 Hz). It can be observed in Figure 43 a slight difference on the transfer function spectral values for different pavement surfaces. However, the largest differences in levels are found at both the lowest and highest frequencies of the range of interest. It can also be observed that the transfer function corresponding to concrete pavement section PCC-1d shows lower spectral values than the rest of the results. Additionally, the transfer function for the reference pavement (U.S. Route 460) shows lower levels than the rest of the transfer functions at very low frequencies. However, this is below the lowest frequency of the range of interest.

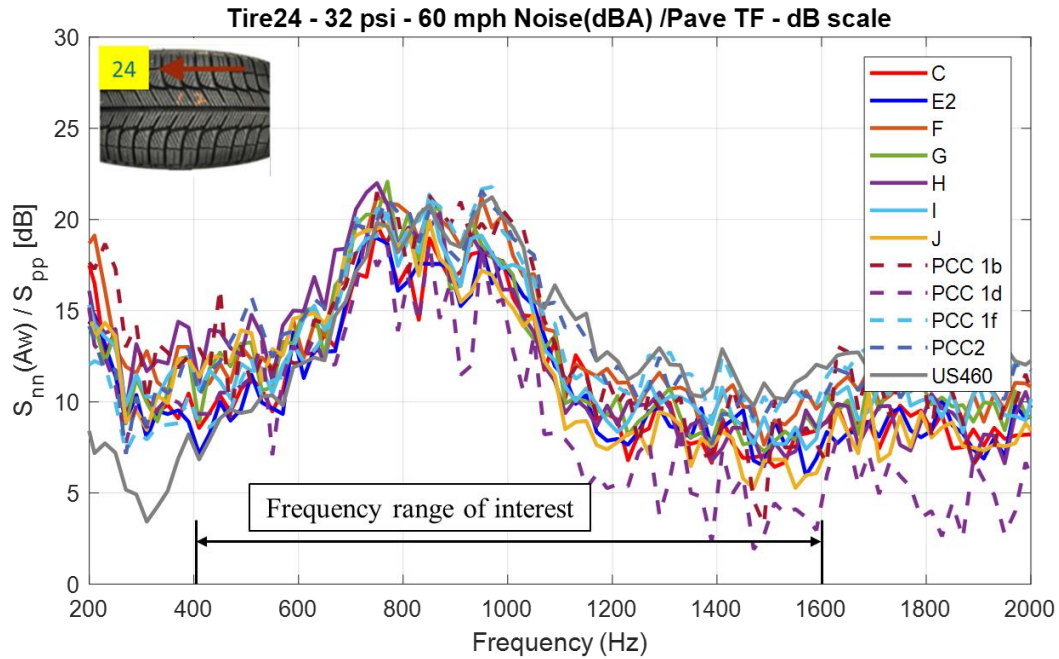


**Figure 43:** NTPN spectrum - pavement profile spectrum transfer functions for Tire 24 for a vehicle speed of 60 mph for different non-porous pavements. Frequency resolution: 20 Hz.

The same comparison between transfer functions is made for the same tire, but for a vehicle speed of 45 mph. Overall, the shape of the transfer function for different non-porous pavement surfaces look similar. Once again, there is slight difference between spectral levels for different pavement surfaces. In addition, the transfer function for concrete section PCC-1d shows again lower spectral levels than the rest of pavement surfaces. It is clear that the levels of the transfer functions computed at 45 mph are lower than the ones computed for a vehicle speed of 60 mph. In addition, the similarity between the shape of the transfer functions, and the closeness between spectral levels suggests that the relationship between the NTPN and the pavement profile does not significantly change from one non-porous pavement surface to another within the frequency range of interest.

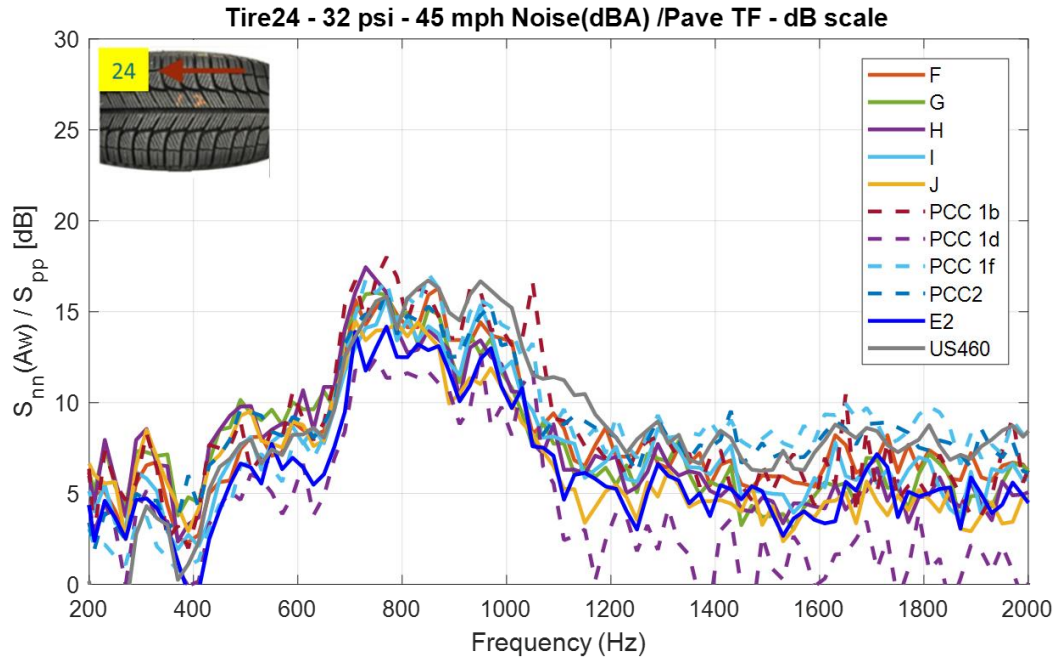


**Figure 44:** NTPN spectrum - pavement profile spectrum transfer functions for Tire 24 for a vehicle speed of 45 mph for different non-porous pavements. Frequency resolution: 20 Hz.

The next step is to compute and study the R function using the data obtained on the different non-porous porous pavement surfaces on the VTTI SMART road and the U.S Route 460 road. Figure 45 shows the R function computed for Tire 01 on pavement section E2 for multiple vehicle speeds. The shape of the function is similar for different vehicle speeds. It can be observed that the R function is higher than 1 for the lower frequencies of the spectrum, and below 1 for higher frequencies. The spectral values of R look similar for speeds of 45, 50 and 55 mph. However, the R function computed for 60 mph show a slight increase compared to the rest of the vehicle speeds.

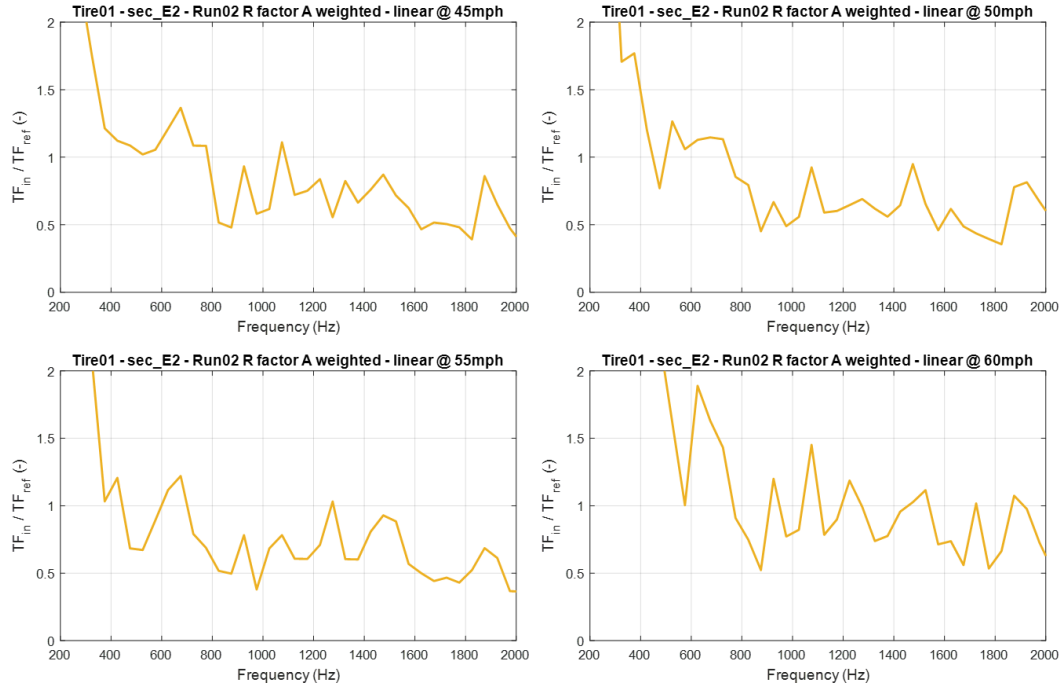


**Figure 45:** R function computed for Tire 01 on pavement section E2 (dense graded mix) at vehicle speeds of 45, 50, 55, and 60 mph. Frequency resolution: 50 Hz.

The same comparison is made for Tire 22 on pavement section J and shown in Figure 46, and for Tire 20 (SRTT) on concrete pavement section PCC-1b, as shown in Figure 47. The shape of the R function for these two figures looks similar to the one observed in Figure 45.

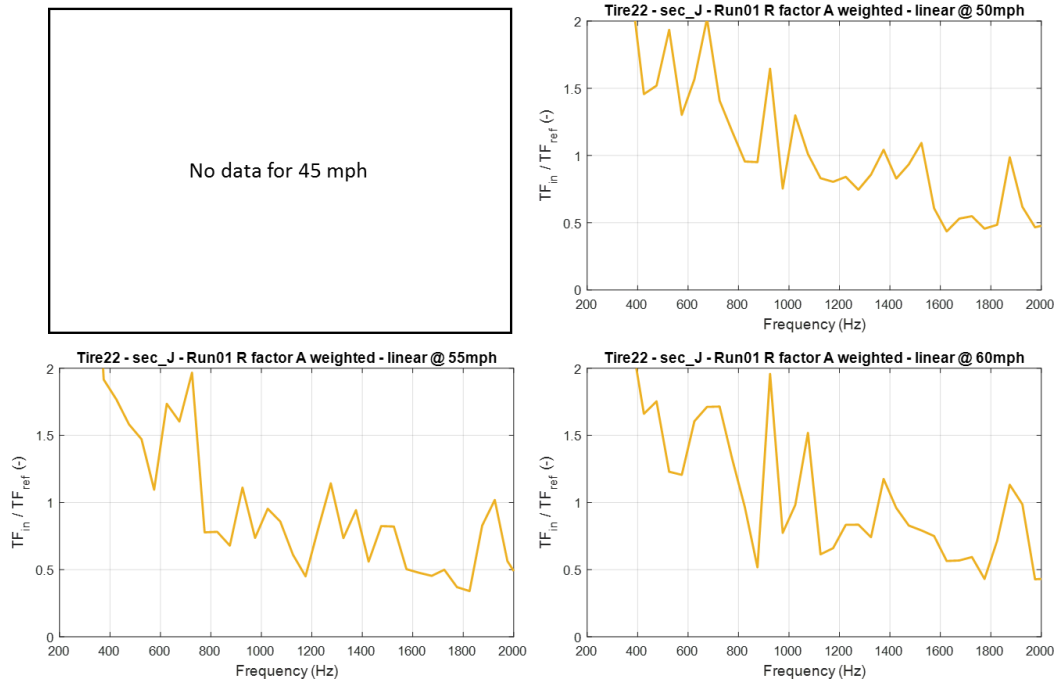


**Figure 46:** R function computed for Tire 22 on pavement section J (dense graded mix) at vehicle speeds of 50, 55, and 60 mph. Frequency resolution: 50 Hz.

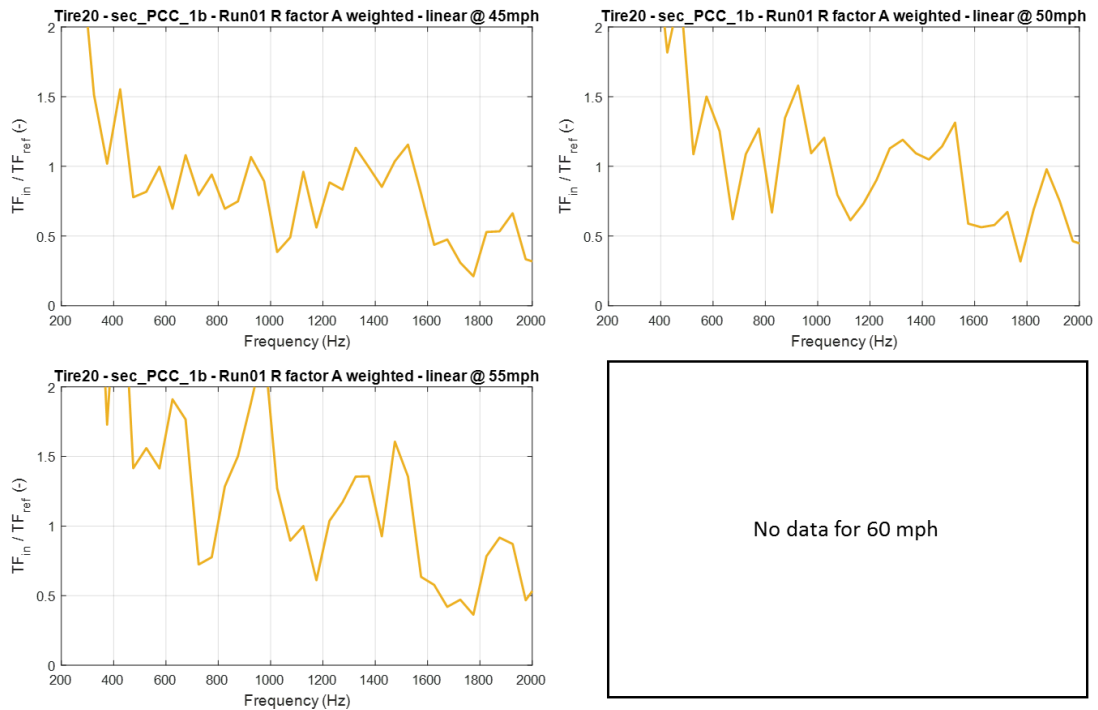


**Figure 47:** R function computed for Tire 20 on pavement section PCC-1b (concrete pavement surface) at vehicle speeds of 45, 50, and 55 mph. Frequency resolution: 50 Hz.

Overall, it is observed that the values of the R function tend to be higher than 1 for low frequencies (approximately below 800-1000 Hz), and less than 1 for higher frequencies (above 800-1000 Hz). This is a strong indicator that:

- For low frequencies (below ~ 800-1000 Hz) the relationship between the texture levels and the NTPN is directly proportional. In other words, an increase on the pavement texture levels results in an increase on the NTPN levels at low frequencies, and a decrease on the texture levels results in a decrease on the NTPN levels.
- On the other hand, for high frequencies (above ~ 800-1000 Hz), the relationship between the texture levels and the NTPN is inversely proportional. Therefore, an increase on the texture levels is translated into a decrease on the NTPN levels at high frequencies, and a decrease on the texture levels results in an increase on the NTPN levels.

The following step is to investigate how the weighting R function defined in Equation 4.7 behaves for:

- each tire tested on the SMART road (see Table 10),
- at each vehicle speed tested (see Table 8),
- on each non-porous pavement section highlighted in Figure 40.

Figure 48 presents a simplified schematic showing the conditions for which the R function is computed and investigated.

$$\bar{R} = \frac{TF_{in-pave}}{TF_{ref-pave}} = \frac{\frac{S_{nn(in-pave)}}{S_{pp(in-pave)}}}{\frac{S_{nn(ref-pave)}}{S_{pp(ref-pave)}}} \left\{ \begin{array}{l} \bullet \text{ Tire 01} \\ \bullet \text{ Tire 09} \\ \bullet \text{ Tire 20 (SRTT)} \\ \bullet \text{ Tire 22} \\ \bullet \text{ Tire 24} \end{array} \right\} \left\{ \begin{array}{l} \bullet \text{ 45 mph} \\ \bullet \text{ 50 mph} \\ \bullet \text{ 55 mph} \\ \bullet \text{ 60 mph} \end{array} \right\} \left\{ \begin{array}{l} \bullet \text{ U.S. Route 460 road} \\ \bullet \text{ 12 pavements from SMART road} \end{array} \right\}$$

**Figure 48:** Tires, vehicle speeds and pavement sections for which the R function was computed and studied.

The weighting R function is computed for the same tire and pavement section but multiple vehicle speeds. Figure 49 shows the R function in linear scale computed for tire 24 on section G and Tire 01 on section J. Overall, it is observed that the shape of the function computed for different vehicle speeds follows the same trend observed in the previous R function plots. Differences on the levels are noticed for different vehicle speeds at low frequencies (~400-600 Hz). There is also a slight difference between the levels around ~1500 Hz.

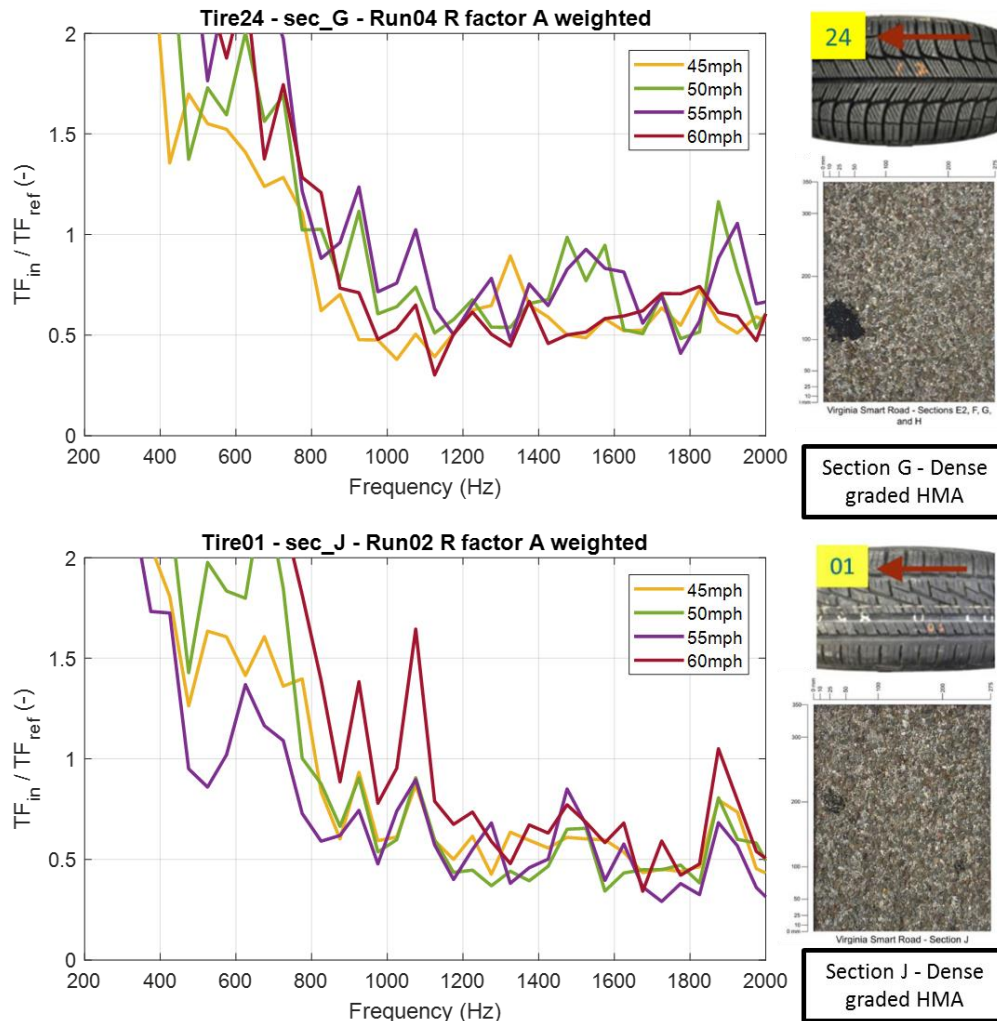


**Figure 49:** R function computed for Tire 24 on section G and Tire 01 on section J at different vehicle speeds. Frequency resolution: 50 Hz.

Figure 50 shows the R function computed for Tire 24 on different pavement surfaces at multiple vehicle speeds.

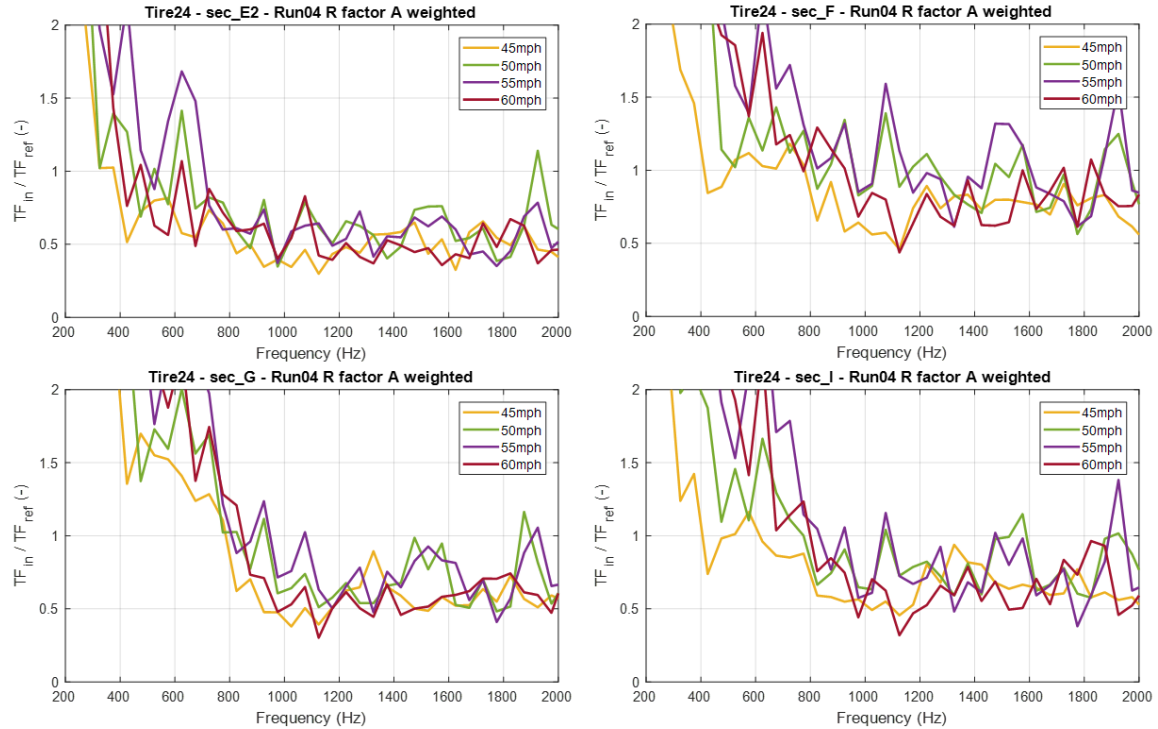


**Figure 50:** R function computed for Tire 24 on different pavement sections at different vehicle speeds. Frequency resolution: 50 Hz.

For the rest of the tires and pavement surfaces tested, the R function computed for different vehicle speeds show similar shapes. Slight differences on the spectral levels are observed for certain cases. However, for practical purposes, it is reasonable to assume that the R function is independent of the vehicle speed.

The next step is to study the behavior of the R function for the different tires tested (similar size but different tread pattern rubber hardness). Figure 51 shows plots comparing the R function in linear scale for the different tires tested on sections E2 and I at 45 mph. The shape of the R function for the rest of the tires (different tire tread rubber hardness) look similar for most of the frequencies within the range of interest. Tire 20 shows higher spectral levels around 1300 Hz.

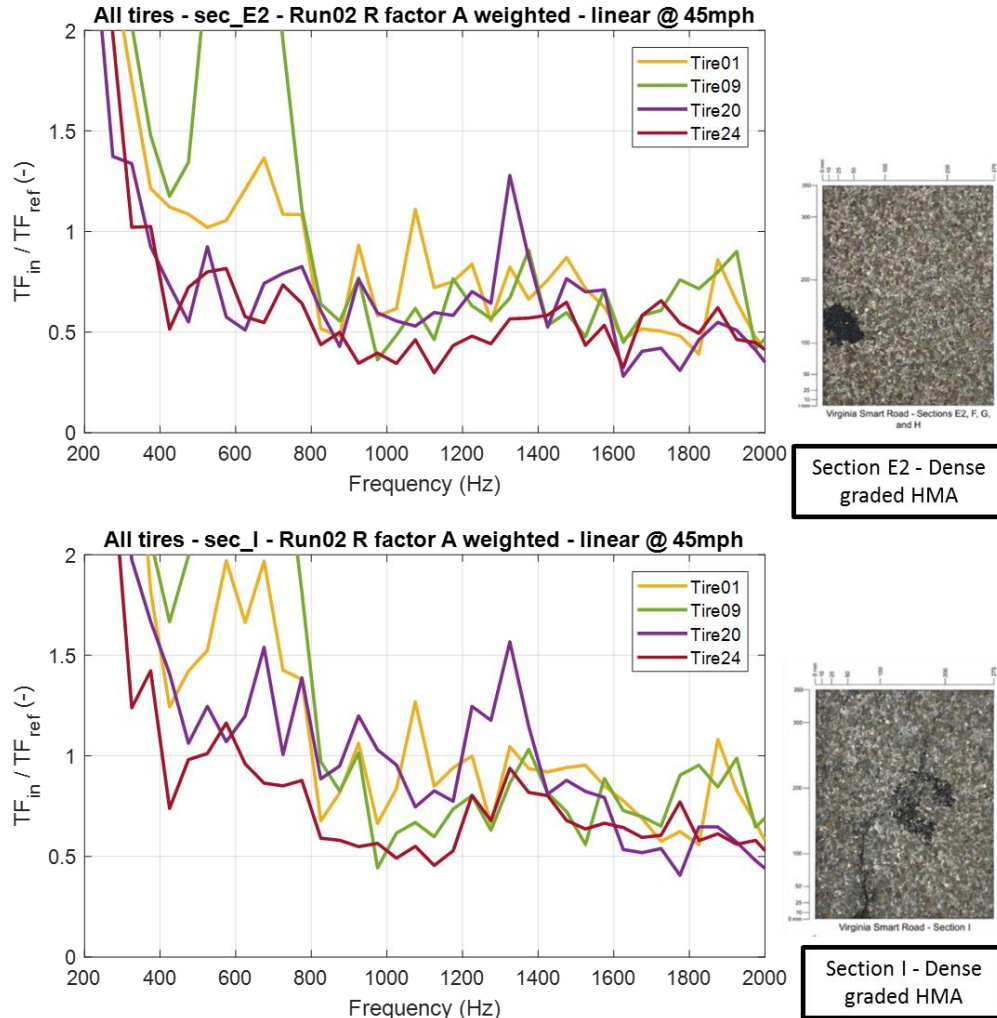


**Figure 51:** R function computed for all tires (except Tire 22) on section E2 and section I for a vehicle speed of 45 mph. Frequency resolution: 50 Hz.

There are also slight differences on the spectral levels of the R function for the different tires. Figure 52 shows the R function computed for different pavement sections at 45 mph for the different tires. The shape of the R function remains similar for the different cases shown, along with small differences between the spectral levels. This behavior is observed when comparing the different tires on the different pavement sections at different speeds. However, considering the extensive hardness range of the tires tested (63 – 75 Shore A) and the results depicted in Figure 52, it can be assumed that the R function is not significantly affected by the tire tread pattern rubber hardness. Figure 52 shows the R function computed for different pavement sections and different tires at 45 mph. When

comparing the four plots, it can be observed that the shape of the R function for the different pavement sections is similar.

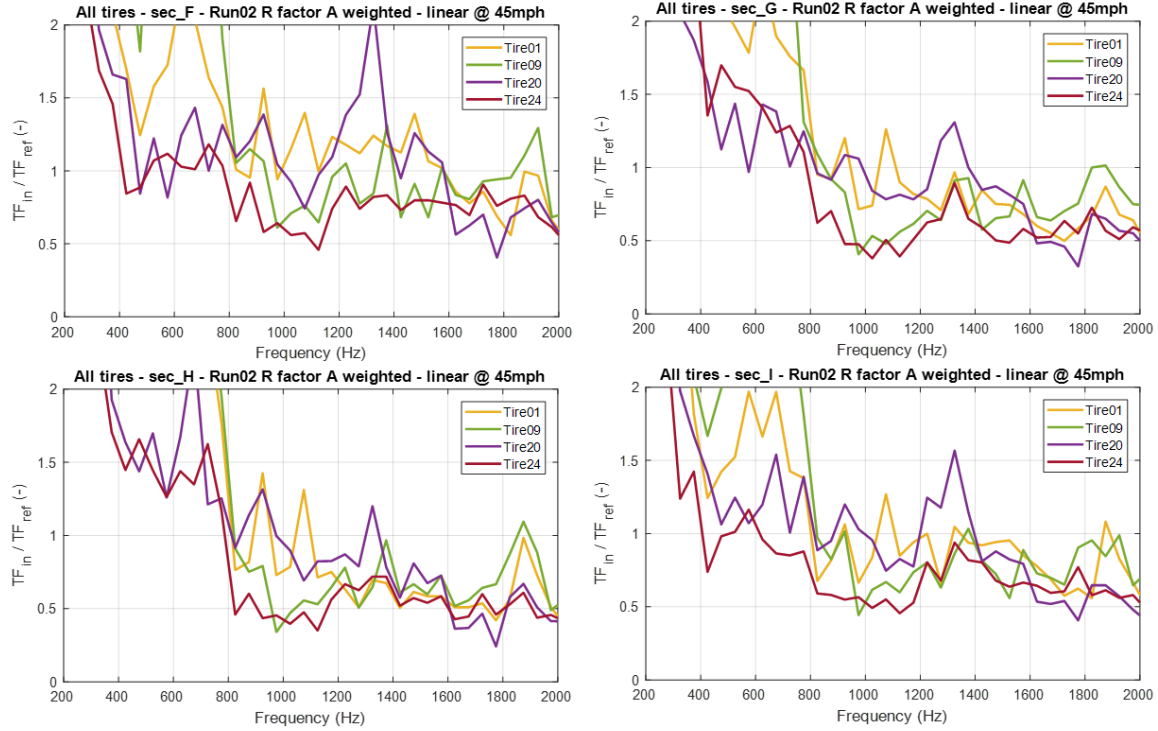


**Figure 52:** R function computed for different tires on different pavement sections at 45 mph. Frequency resolution: 50 Hz.

Although there are differences on the spectral levels for the different R functions computed for different tires, pavement sections and vehicle speeds, these differences are considered to be small for practical purposes. In order to implement the correcting function proposed in Subsection 4.1.2, an R function must be defined. Computing  $\bar{R}$  by averaging all the data available (R function for all the tires, vehicle speeds and non-porous pavement sections investigated) is considered to be a good practical approach to implement the NTPN correction approach. To this end, R is estimated as

$$\bar{R}(f_j) = \frac{1}{Nb_{sections}} \cdot \frac{1}{Nb_{tires}} \cdot \frac{1}{Nb_{speeds}} \cdot \sum_{s=1}^{Nb_{sections}} \sum_{t=1}^{Nb_{tires}} \sum_{i=1}^{Nb_{speeds}} \frac{TF_{(in-pave)}(section, tire, speed, f_j)}{TF_{(ref-pave)}(tire, speed, f_j)} \quad (4.9)$$

In Equation 4.9, the R function is computed at each frequency  $f_j$  averaging the values for:

- 12 non-porous pavement sections considered in this study (i.e.,  $Nb_{sections}$ ),
- 4 tires tested on the SMART road (i.e.,  $Nb_{tires}$ ), and
- 4 speeds tested on the SMART road (i.e.,  $Nb_{speeds}$ ).

Figure 53 shows the averaged R function points as a function of frequency obtained from Equation 4.9. The  $\bar{R}$  function is approximated using a 3-term Gaussian curve. This curve provided the lowest error ( $R^2 = 0.974$ ) when fitting the data within the frequency range of 200 – 2000 Hz. The expression for the fitting curve is

$$\bar{R}_{(f)} = a_1 \cdot e^{-\left(\frac{(f-b_1)}{c_1}\right)^2} + a_2 \cdot e^{-\left(\frac{(f-b_2)}{c_2}\right)^2} + a_3 \cdot e^{-\left(\frac{(f-b_3)}{c_3}\right)^2} \quad (4.10)$$

with the coefficients listed in Table 12.

| Table 12: 3-term Gaussian curve fitting terms |                     |       |          |       |        |
|-----------------------------------------------|---------------------|-------|----------|-------|--------|
| Term                                          | Value               | Term  | Value    | Term  | Value  |
| $a_1$                                         | $1.338 \times 10^9$ | $a_2$ | -0.01075 | $a_3$ | 0.8807 |
| $b_1$                                         | -8815               | $b_2$ | 411.4    | $b_3$ | 5238   |
| $c_1$                                         | 2041                | $c_2$ | 3.561    | $c_3$ | 7278   |

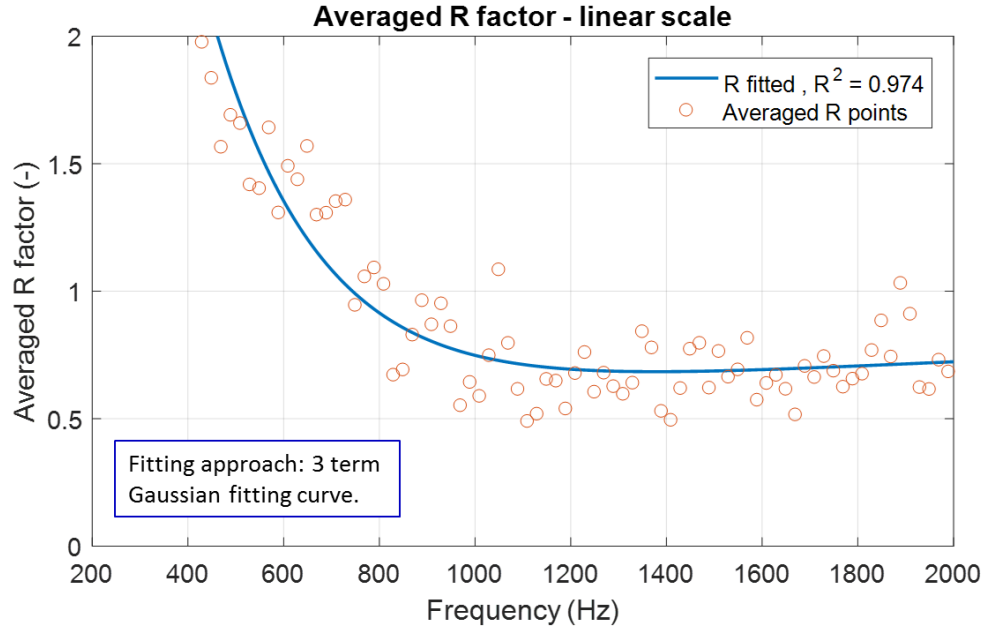


**Figure 53:** Points for the averaged R function in linear scale, and 3-term Gaussian fitting curve.

The next step is to validate the approach proposed to account for the pavement in the prediction of the NTPN. This is presented in the following section.

## 4.2 Results and validation

As mentioned before, the main objective of this chapter is to implement an approach to modify the NTPN from the reference pavement to any other input pavement knowing the relationship between the reference and the input pavement profiles. In this section we present the results of implementing the approach proposed in the previous subsection 4.1.3.

Figure 54 shows a comparison between the measured NTPN and the corrected NTPN using the proposed pavement scaling approach. The results are presented for Tire 01 on section G for multiple vehicle speeds (45, 50, 55, and 60 mph).

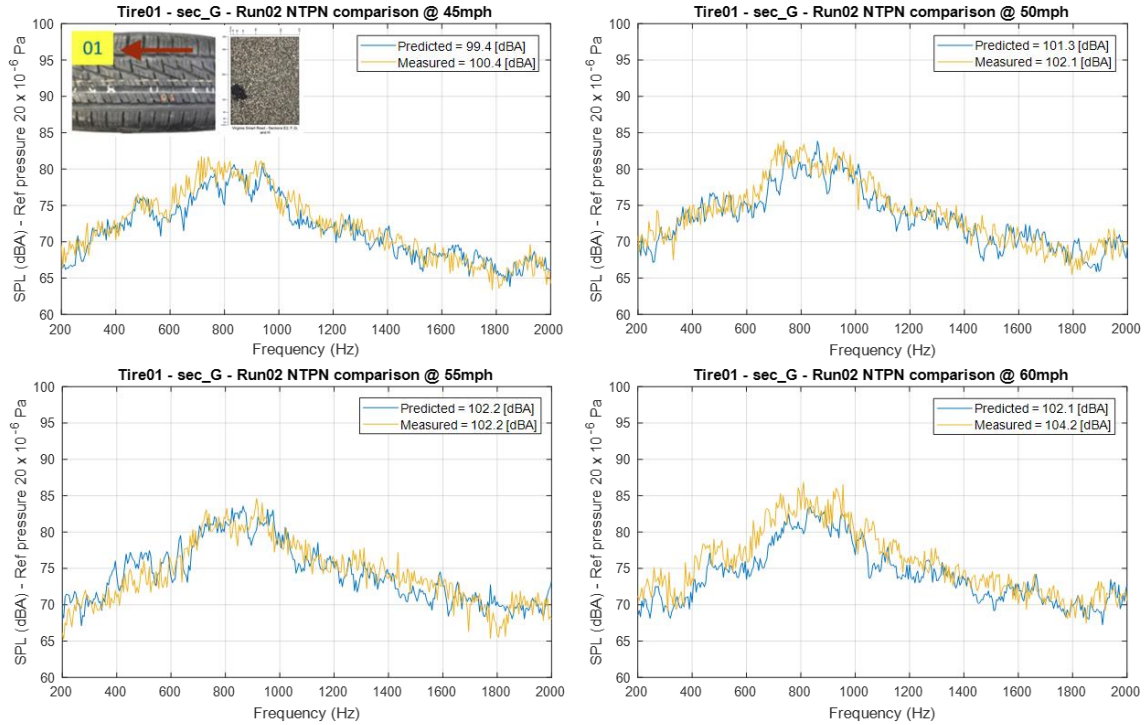


**Figure 54:** NTPN spectrums comparison between measured and predicted by current approach. Tire 01 – Section G – Vehicle speeds: 45-50-55-60 mph. Frequency resolution 5 Hz.

For most of the vehicle speeds, the predicted NTPN is very close to the measured NTPN spectrum. In the case of 45, 50 and 55 mph, the approach does a good job for all frequencies. For the frequency range of 600 – 800 Hz the predicted NTPN is slightly below the measured values. Still, the differences on levels are small. For the high frequency end of the spectrum the predicted and measured NTPN match fairly well. The predicted NTPN spectrum for 60 mph is below the measured NTPN spectrum levels for most of the frequency range of interest.

The same comparison is made for Tire 24, on section PCC-1b, as shown in Figure 55. It is observed that the shape and levels of the predicted and measured values match fairly well for all speeds.

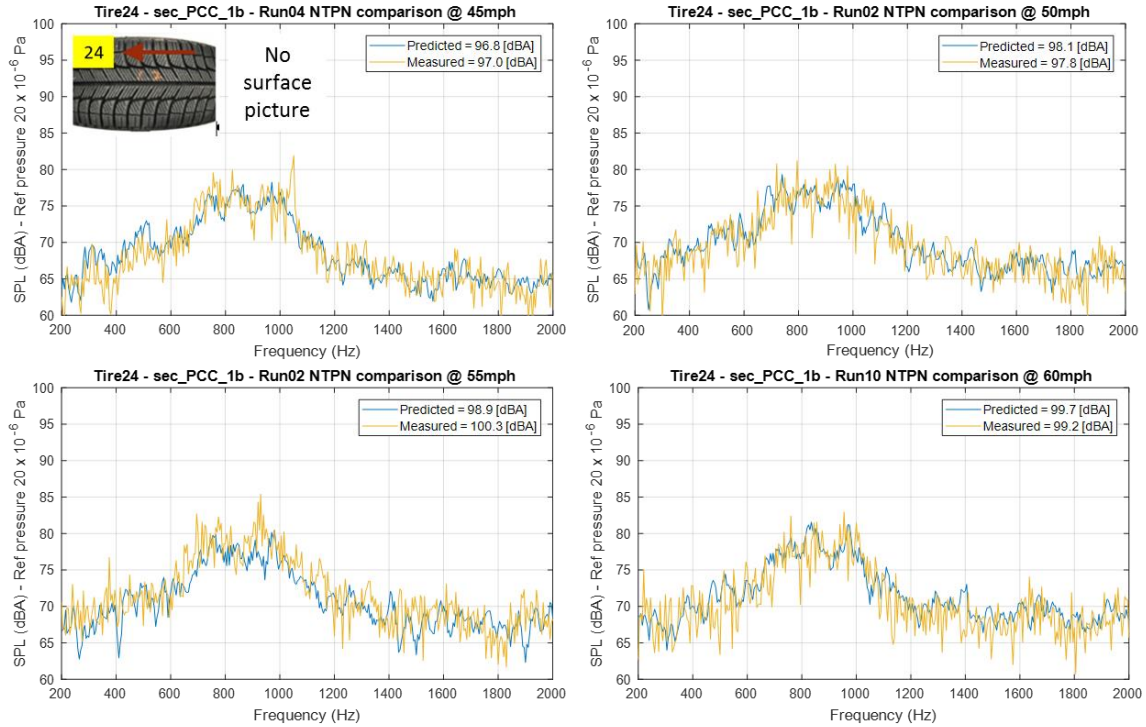


**Figure 55:** NTPN spectrums comparison between measured and predicted by current approach. Tire 24 – Section PCC-1b – Vehicle speeds: 45-50-55-60 mph. Frequency resolution 5 Hz.

The OASPL for the cases in Figure 54 and Figure 55 also shows very good agreement between prediction and measurements. Figure 56 shows the comparison between measured and predicted OASPL NTPN. The average OASPL error between the measured and predicted NTPN is 1.2 dBA, which it is considered to be acceptable.

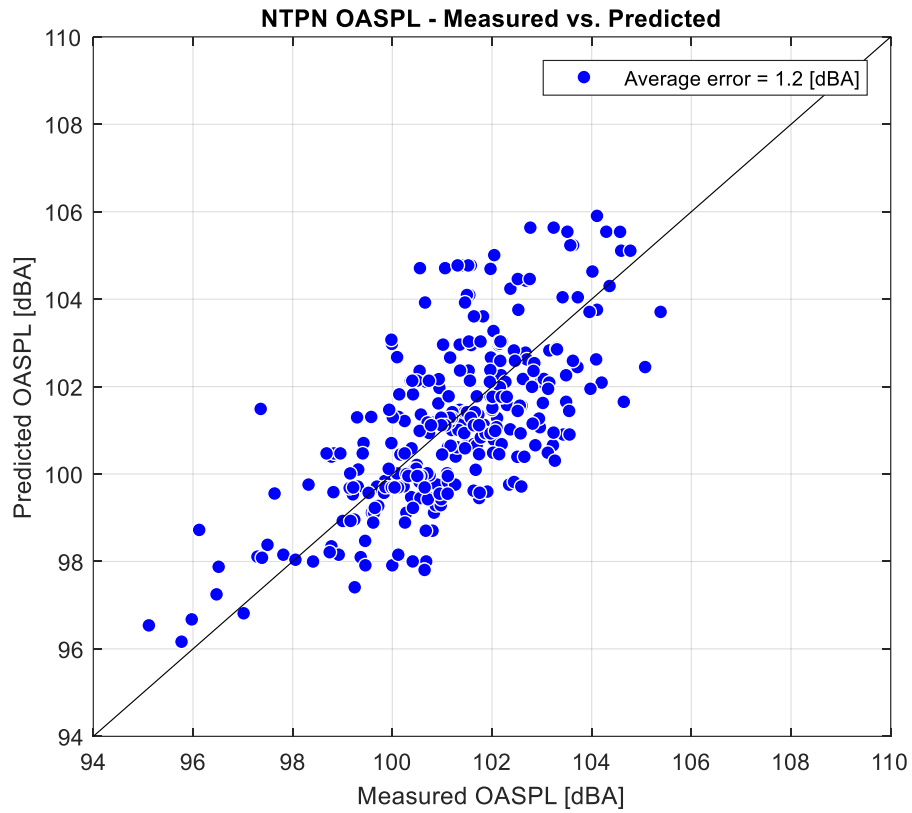


**Figure 56:** NTPN OASPL comparison between measured and predicted by the proposed approach.

The final step is to incorporate the NTPN pavement scaling module presented in this chapter into Li's model, and investigate the results obtained when compared to experimental data. This is done in the following chapter.

## 5 Full TPIN prediction model

This chapter introduces the full model to predict TPIN using both tire and pavement parameters as inputs. The TPIN prediction model presented in this chapter is based on the model presented by Li (2017). However, it introduces two main modifications to his model. They are:

- the implementation of the hybrid neuron configuration to predict only positive values on the two ANNs, and
- the addition of the NTPN pavement scaling module presented in Chapter 4. This allows to account for the pavement profile as input when predicting the NTPN.

This chapter is organized as follows. First, the structure of the final TPIN prediction model is introduced and its modules are briefly described. In addition, the model specifications and limitations are explained. Moreover, the validation for the model taking into account only tire parameters is presented (this allows to evaluate the results obtained by implementing the non-negative ANN configuration only, without the NTPN pavement scaling module). Finally, the results for the complete model (i.e., using both tire and pavement parameters as inputs) are presented and discussed.

## 5.1 Final model

The complete model to predict TPIN based on tire and pavement parameters is presented in Figure 57. This model implements two ANNs (see Table 3). One ANN predicts the TPN order spectrum at a fixed vehicle speed (i.e., 60 mph). Then, the predicted TPN is scaled to any arbitrary vehicle speed using the tire size and a speed exponent scaling law, resulting in the final TPN frequency spectrum. The second ANN predicts the NTPN frequency spectrum for a fixed reference tire size (i.e., 215/60R16) and a fixed pavement surface (i.e., U.S. Route 460, where the experimental data to train the ANNs was acquired). Then, the NTPN predicted by the ANN is corrected for an input pavement surface using the approach explained in subsection 4.1.2. Additionally, the NTPN component is scaled to any given arbitrary tire size using a relationship based on the input and the reference tire carcass width. Finally, both components are added resulting in the total tire noise spectrum.

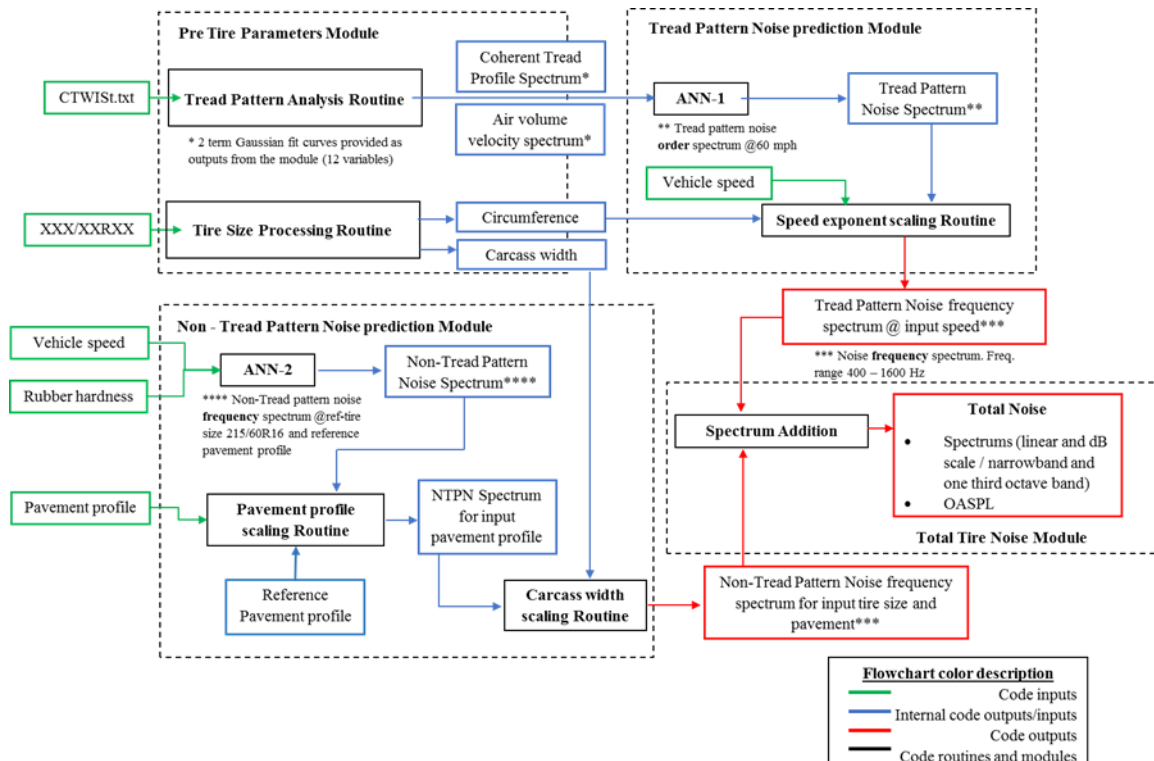


**Figure 57:** Full TPIN prediction model based on tire and pavement parameters.

In Figure 57, the main inputs to the model are highlighted with the green color, and they are the following:

- The scanned tire tread pattern information using a CTWIST (Circumferential Tread Wear Imaging System) format file (Feng, 2017).
- The tire size commercial denomination (e.g., 215/60R16).
- The vehicle speed at which the TPIN is meant to be predicted in mph.
- The tire tread pattern rubber hardness in shore A.
- The one-dimensional pavement profile for the non-porous surface for which the TPIN will be predicted.

The final model is divided into five main modules, as shown in Figure 58. The main task of each module is briefly described in Table 13.

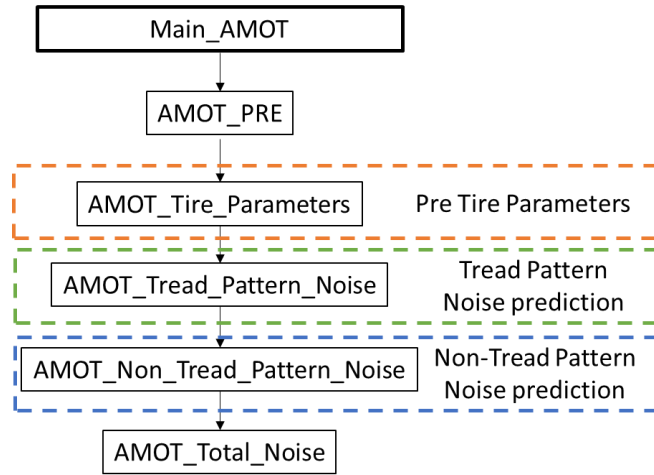


**Figure 58:** Main modules of the final AMOT model.

| Table 13: Main modules tasks description |                                                                                                                                                                                                                                                                                        |
|------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Module                                   | Main task                                                                                                                                                                                                                                                                              |
| <b>Pre</b>                               | Checks the inputs files. It requests inputs and loads the necessary data to run the code.                                                                                                                                                                                              |
| <b>Tire Parameters</b>                   | Processes multiple tire parameters to be used by the code. It also processes the Circumferential Tread Wear Imaging System (CTWIST) file containing the scanned tire tread pattern information. Additionally, it processes the tire size parameters from the tire's size denomination. |
| <b>Tread Pattern Noise (TPN)</b>         | Uses the tread pattern and tire size parameters to predict TPN in narrowband and one-third octave band spectrums. Parameters such as tire circumference and vehicle speed are also used.                                                                                               |
| <b>Non-Tread Pattern Noise (NTPN)</b>    | Uses the tire hardness and tire size to predict the NTPN in narrowband and one-third octave band spectrums. Parameters such as carcass width, vehicle speed, and pavement profile data are also used.                                                                                  |
| <b>Total Noise (TTN)</b>                 | Adds the TPN and NTPN spectrums previously computed. It obtains the Total Tire Noise (TTN) narrowband and one-third octave band frequency spectrums.                                                                                                                                   |

In the following sections the validation of the final model is presented.

## 5.2 Model validation using only tire parameters

Since the data collected at different pavement surfaces is limited (SMART road test), the model introduced in this chapter is first validated without using the NTPN pavement scaling module. This allows to use the larger amount of data collected at the U.S Route 460 to validate the performance of both ANNs implemented by the model (i.e., neurons using the hybrid configuration proposed in subsection 2.2.4). Table 14 shows the division of the tire noise data acquired in the U.S. Route 460 used to train both ANNs. The same eight tires are used in both ANNs test sets (i.e., to validate the model).

| Table 14: Tires used for both ANNs training. |                                                                   |                            |                            |
|----------------------------------------------|-------------------------------------------------------------------|----------------------------|----------------------------|
| Set                                          | Training                                                          | Validation                 | Test                       |
| ANN1 for Tread Pattern Noise prediction      |                                                                   |                            |                            |
| Number of tires                              | 13                                                                | 4                          | 8                          |
| Tires                                        | 01 02 03 04 05 06 07 08<br>10 11 13 17 19                         | 12 14 16 20                | 09 15 18 22 23 45<br>49 55 |
| ANN2 for Non Tread Pattern Noise prediction  |                                                                   |                            |                            |
| Number of tires                              | 20                                                                | 9                          | 8                          |
| Tires                                        | 02 03 04 05 07 12 13 14<br>17 19 20 24 25 29 37 39<br>42 53 54 57 | 01 06 08 10 11 16 26 27 43 | 09 15 18 22 23 45<br>49 55 |

The outputs of the ANNs in the model presented in Figure 57 are:

- ANN1 predicts the TPN order spectrum for a vehicle speed of 60 mph (order range: 40-120).
- ANN2 predicts the NTPN frequency spectrum for a reference tire size (i.e., 215/60R16) and a reference pavement surface (i.e., U.S. Route 460).

In order to demonstrate that the new ANN configuration is able to predict only positive values, each ANN (ANN1 and ANN2) is trained using: I) the classic fitting configuration (symmetric sigmoid and pure linear transfer function), and II) the hybrid configuration to predict only positive values (see subsection 2.2.4). Figure 59 shows the predicted TPN results by ANN1 for two tires belonging to the test set (i.e., Tire 09 and Tire 15). The linear

scale spectrum is preferred since the presence of negative values would make the decibel scale not adequate.

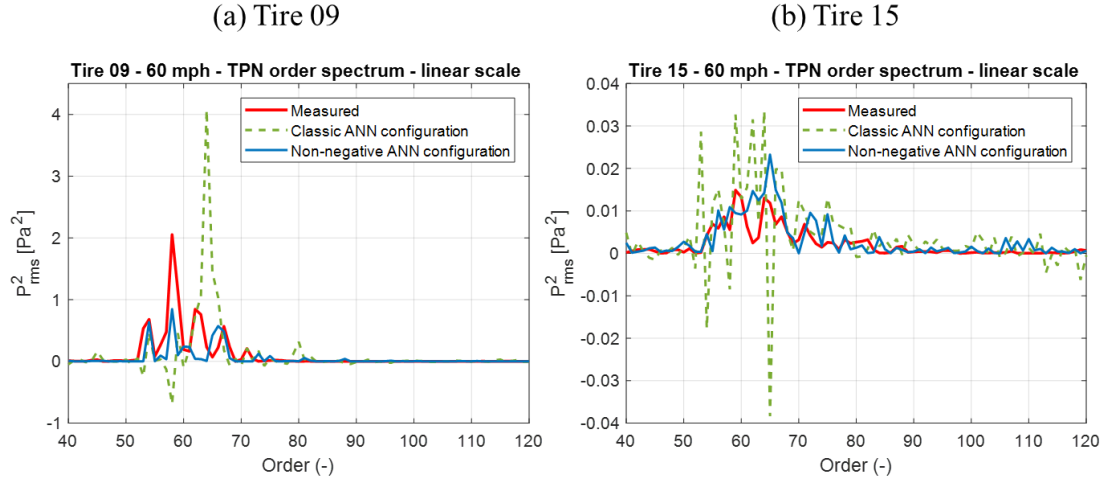


**Figure 59:** TPN order spectrum comparison in linear scale for a classic and the non-negative ANN configuration for (a) Tire 09 and (b) Tire 15.

The plots clearly demonstrate that the classic fitting ANN configuration predicts negative acoustic sound pressure values at certain orders of the spectrum (i.e., physically wrong results). On the other hand, the new hybrid configuration proposed in Chapter 2 predicts only positive values. Figure 60 shows the comparison for the same tires. However, the NTPN predictions made by ANN2 are presented.

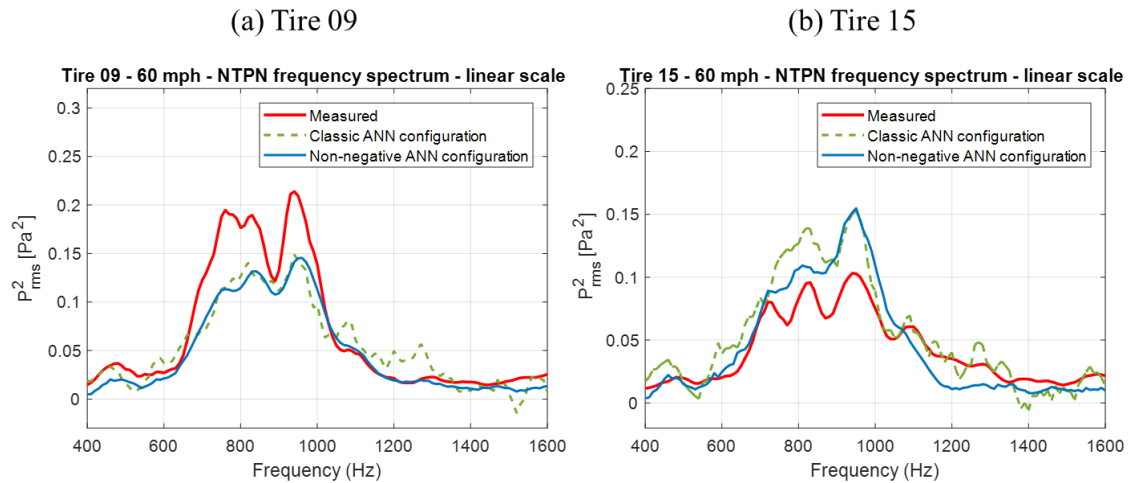


**Figure 60:** NTPN frequency spectrum comparison in linear scale for a classic and the non-negative ANN configuration for (a) Tire 09 and (b) Tire 15.

In this case, the negative values predicted by the classic configuration are not as prevalent as in the TPN case. However, the classic ANN fitting configuration still predicts negative acoustic pressure values at certain frequencies of the spectrums. The same as the TPN case, the hybrid ANN configuration predicts only positive values. Therefore, the new hybrid configuration successfully fulfills the requirement for which it was designed for: to predict only positive values.

The next step is to compute the results for the complete model using only tire parameters, and compare them to the experimental data available from the U.S. Route 460. Figure 61 shows the comparison between the measured tire noise data and the predicted results by the model for Tire 09 (winter tire) at multiple vehicle speeds. There is good agreement between the measured noise and the predicted tire noise.

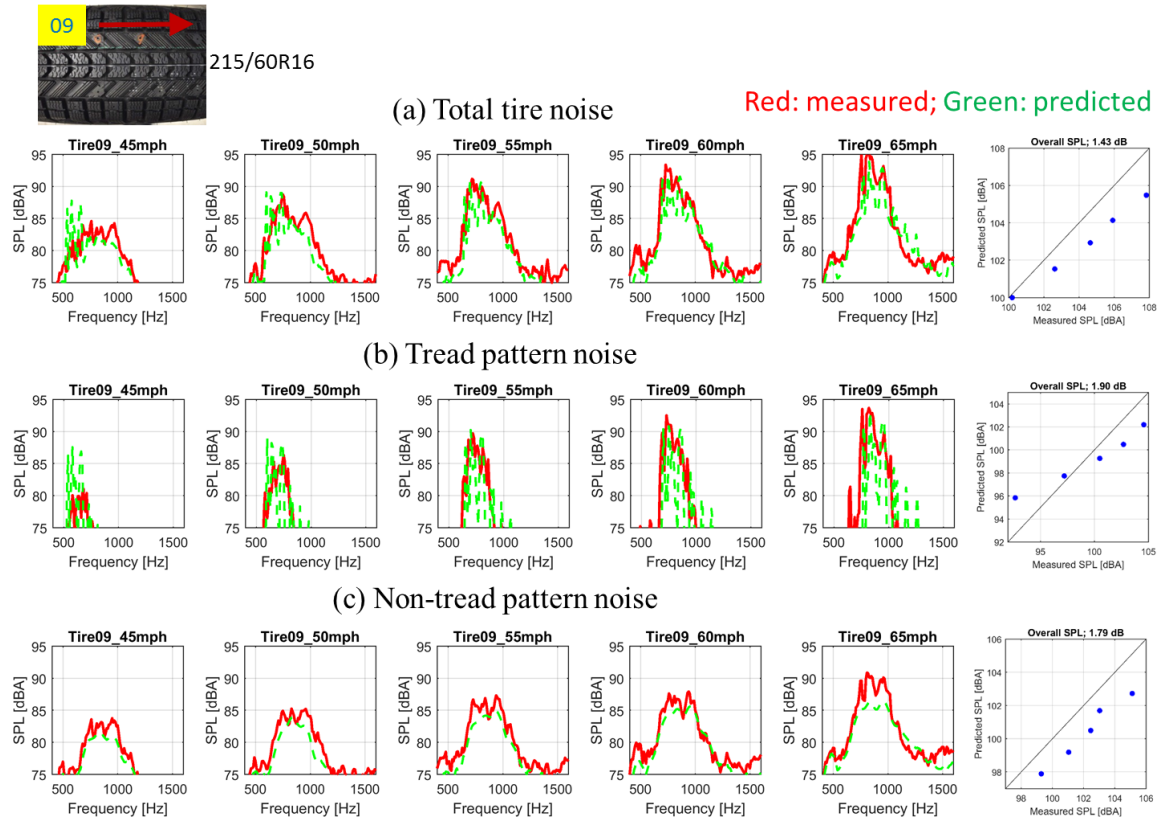


**Figure 61:** TTN, TPN and NTPN spectrums and OASPL comparison between measured and predicted data for Tire 09 at multiple vehicle speeds. Frequency resolution: 10 Hz.

Figure 62 shows the same comparison as the previous figure, but for Tire 23. There is also good agreement between the measured and predicted noise. The results for the rest of the test tires are presented in Appendix E.

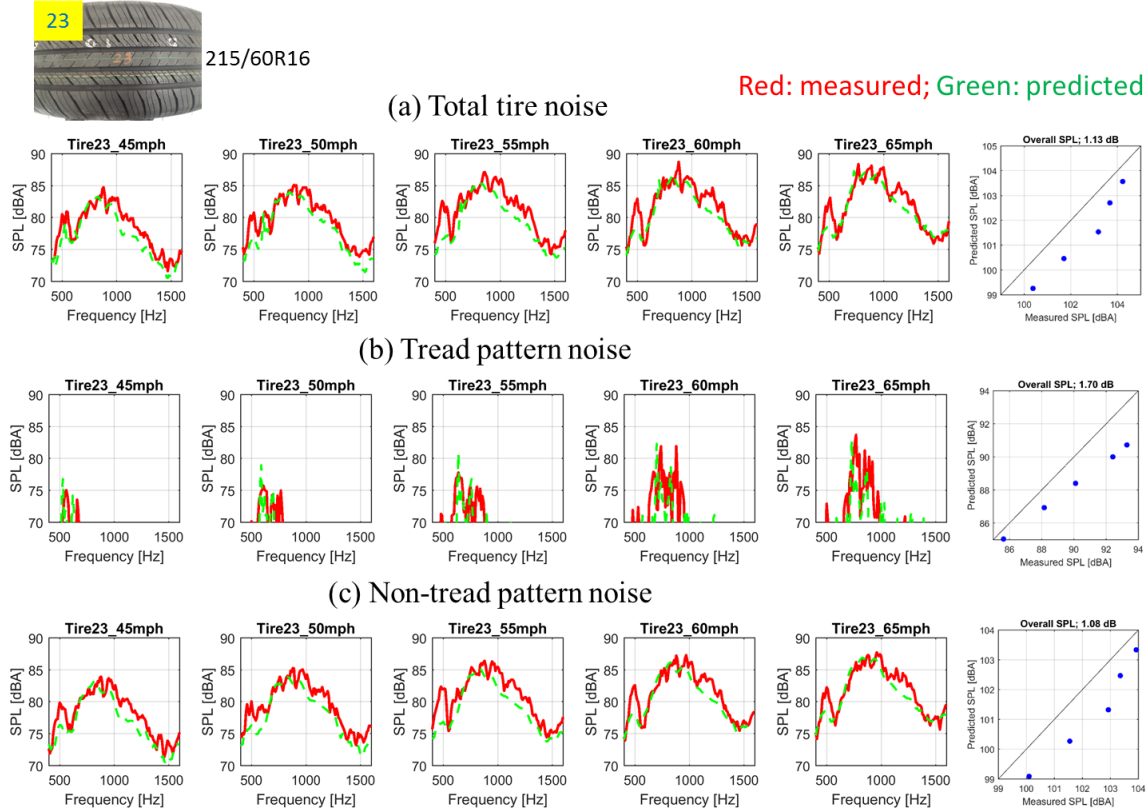


**Figure 62:** TTN, TPN and NTPN spectrums and OASPL comparison between measured and predicted data for Tire 23 at multiple vehicle speeds. Frequency resolution: 10 Hz.

Finally, the OASPL between measured and predicted tire noise are compared for the two independent components (i.e., TPN and NTPN) and for the TTN. Figure 63 shows the results for the 8 tires belonging to the test set (see Table 14) at the U.S Route 460 at 5 discrete vehicle speeds.

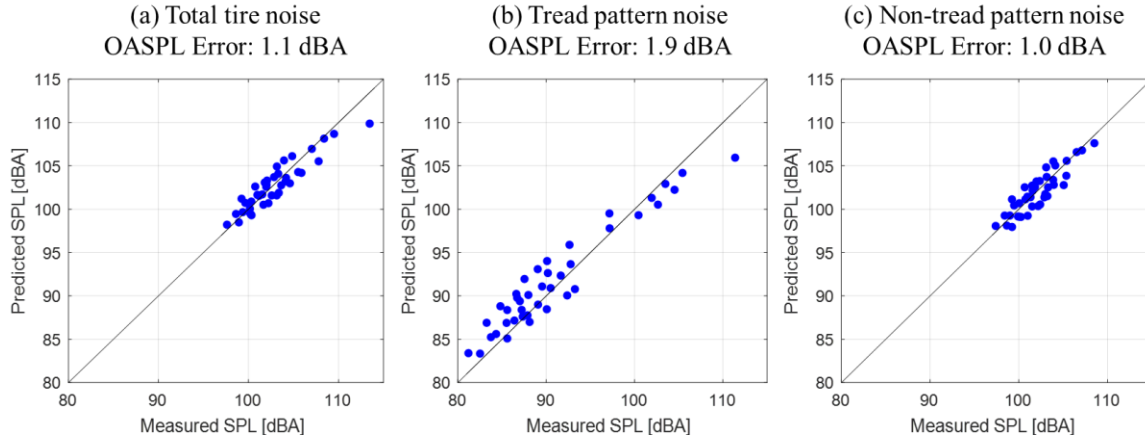


**Figure 63:** Comparison between measured and predicted overall A-weighted sound pressure level (OASPL) for the test tires. (a) Total tire noise, (b) Tread pattern noise, and (c) Non tread pattern noise.

The results presented in Figure 63 show good agreement between the measured and predicted tire noise for the two independent components and the total tire noise. The same results were computed for the classic ANN configuration. They are presented in Appendix A. In Figure 63, the TPN prediction shows the highest overall error (i.e., 1.9 dBA). However, the NTPN component is the one that usually dominates for the tire overall noise. Hence, the NTPN overall error of 1.0 dBA is clearly reflected on the total tire noise overall error of 1.1 dBA which it is considered to be a very good value for the overall error of the model.

Additionally, the TPN and TTN for all test tires are computed and the tires ranked or ordered for increase overall noise levels. This allows to validate the model capability to capture the relative noise levels between the different tires (instead of the accuracy of the noise levels predicted). Figure 64 shows the test tires OASPL TPN ranking at 4 different vehicle speeds. The measured OASPL are used as reference to arrange the tire order from the lowest OASPL (left) to the highest one (right).

## Tread Pattern Noise (TPN) - Test Tires Ranking

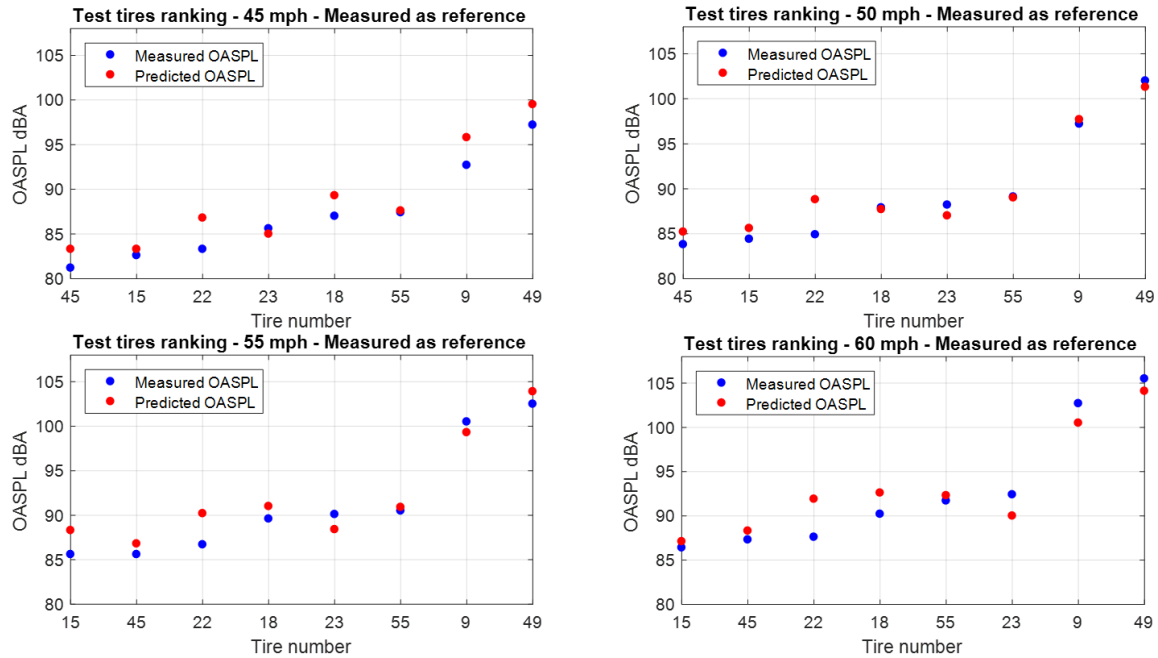


**Figure 64:** Test tires tread pattern noise TPN OASPL ranking for 45, 50, 55 and 60 mph.

The measured TPN tire ranking trend is very well captured by the model. Tire 22 shows a significant difference between the measured and predicted OASPL for most of the vehicle speeds tested. This difference in the noise levels would change its ranking, e.g. at 60 mph from the 3<sup>rd</sup> to the 5<sup>th</sup> quietest tire in the set. Another important observation is that the model is able to capture fairly well the difference in noise levels between the tire producing the lowest TPN and the one producing the highest. This is observed at all the vehicle speeds tested.

The same plots are created to see the TTN OASPL test tire ranking, as shown in Figure 65. The measured TTN tire ranking trend is well captured by the model. Once again, the model is able to capture fairly well the difference in noise levels between the tire producing the lowest TTN and the one producing the highest for all the vehicle speeds. Therefore, the TPN prediction tool presented in this section using only tire parameters is considered to be accurate.

## Total Tire Noise (TTN) - Test Tires Ranking

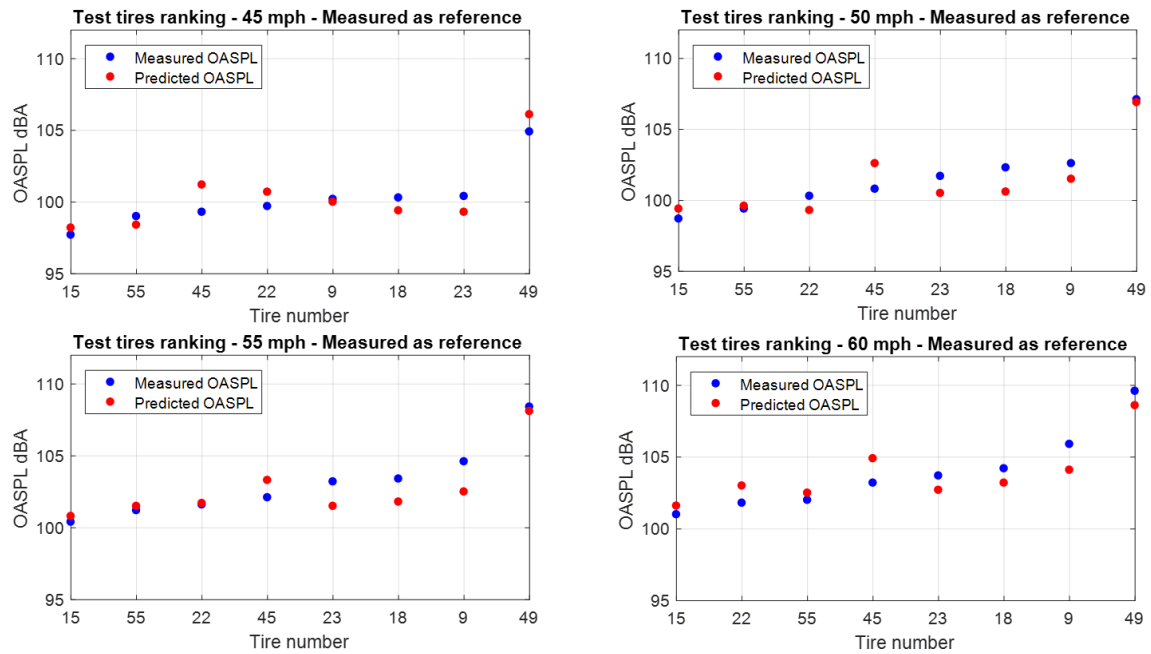


**Figure 65:** Test tires total tire noise TTN OASPL ranking for 45, 50, 55 and 60 mph.

### 5.3 Model validation using both tire and pavement parameters

The last objective in this thesis is to validate the complete model for TPIN prediction using both tire and pavement parameters. The amount of data collected at the SMART road is limited, which makes the validation process challenging. Tire 22 was tested on the SMART road (on different pavement surfaces) and the noise data for Tire 22 was not used to train either of the ANNs (i.e., Tire 22 belongs to both ANNs test set). Therefore, this tire is used for the model validation for multiple pavement surfaces and speeds

The results for Tire 22 are presented for:

- Dense graded mix pavement section G (Figure 66).
- Dense graded mix pavement section C (Figure 67).
- Portland cement concrete section PCC-1b (Figure 68).

Figure 66, Figure 67 and Figure 68 show in red the measured NTPN spectrum, the dashed dark green line indicates the NTPN spectrum predicted for the reference pavement surface and the dark blue line shows the predicted NTPN spectrum corrected for the input pavement profile spectrum. The three figures show results for 50, 55 and 60 mph. Tire noise data for Tire 22 was not collected at 45 mph. Overall, all three figures show good agreement between the measured and predicted NTPN spectrums for Tire 22 on the three specified pavement sections. The NTPN scaling module is capable of correctly adjusting the NTPN levels at very low frequencies of the spectrum ( $\sim 500$  Hz). For the dominant NTPN frequencies ( $\sim 700$ - $1000$  Hz), the adjustment made on the NTPN is fairly accurate for all the vehicle speeds shown. For higher frequencies of the spectrum, the adjustment on the noise levels results in a slight under prediction of the NPTN. Overall, the measured NTPN and the predicted results show good agreement.

Tire 22: 225/60R16  
Tire belongs to test set  
Section G – Dense Graded asphalt

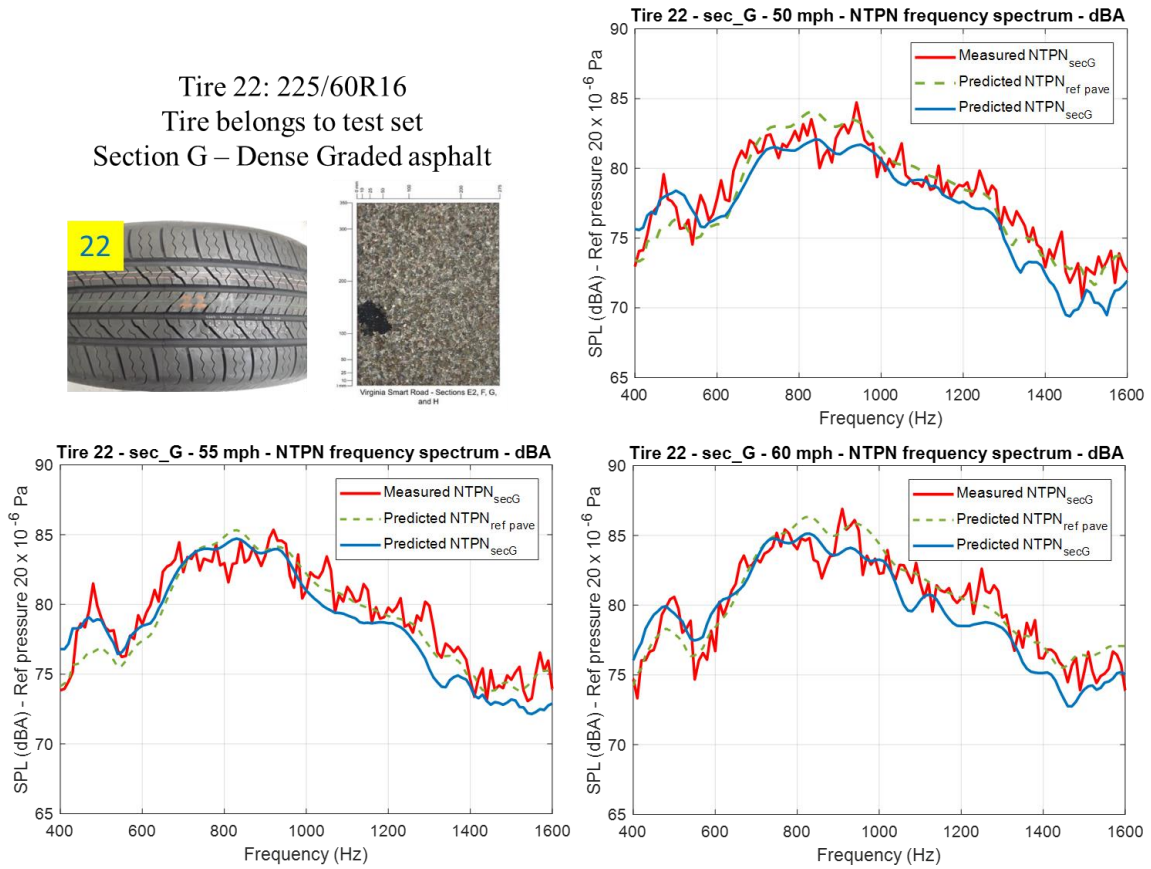


**Figure 66:** NTPN spectrums for Tire 22 on pavement section G for vehicle speeds of 50, 55 and 60 mph. Results shown for measured tire noise, predicted NTPN using only tire parameters, and predicted NTPN using both tire and pavement parameters. Frequency resolution: 10 Hz.

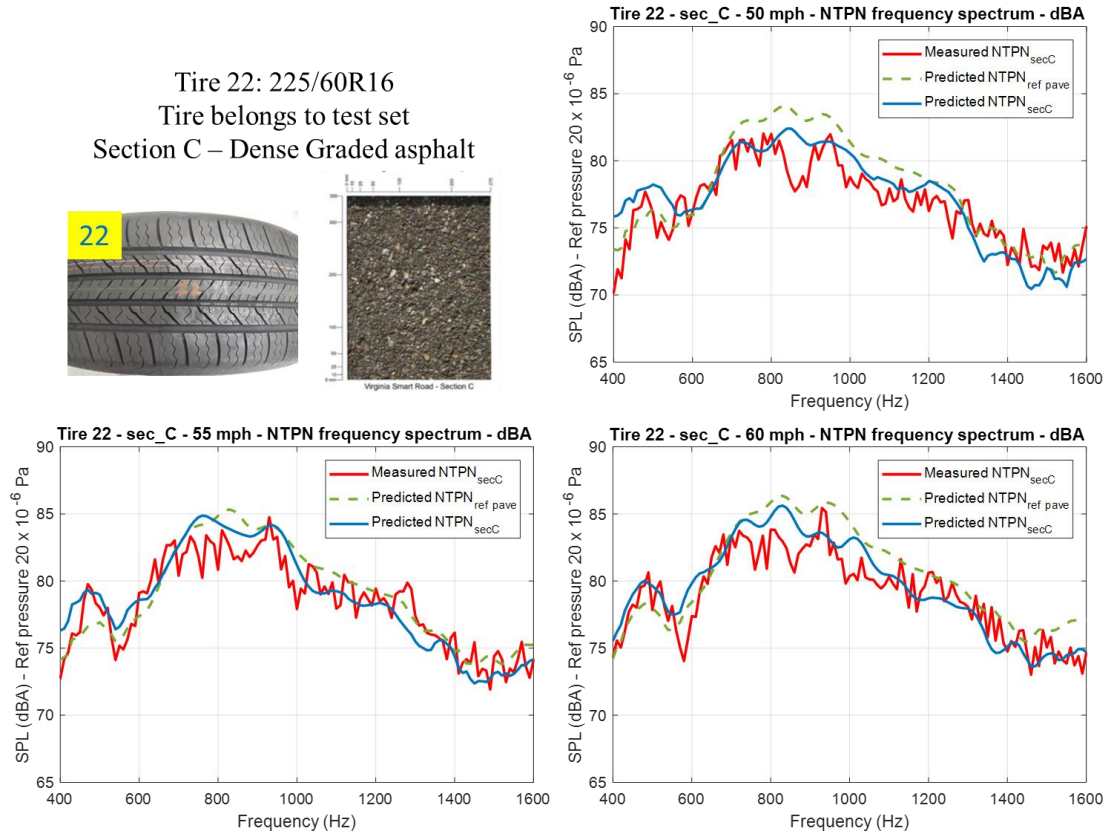


**Figure 67:** NTPN spectrums for Tire 22 on pavement section C for vehicle speeds of 50, 55 and 60 mph. Results shown for measured tire noise, predicted NTPN using only tire parameters, and predicted NTPN using both tire and pavement parameters. Frequency resolution: 10 Hz.

Figure 68 shows good agreement between the measured and predicted NTPN spectrums for Tire 22 on pavement section PCC-1b for a vehicle speed of 50 mph. In the case of 55 and 60 mph, the NTPN correction clearly results in an under prediction of the noise levels. However, the correction made on the NTPN predicted for the reference pavement still tends to decrease the tire noise levels (the correction is applied in the right way).

Tire 22: 225/60R16  
Tire belongs to test set  
Section PCC 1b – Concrete surface



No  
surface  
picture

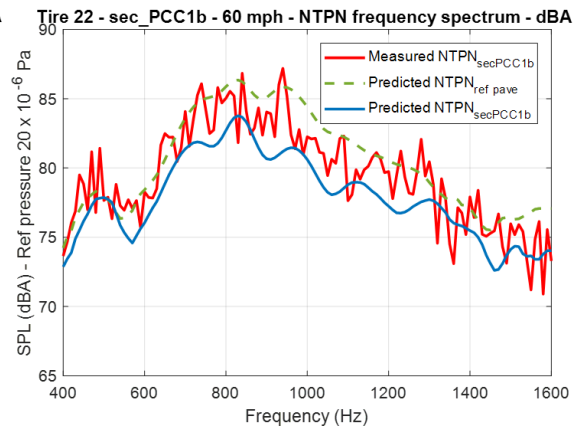
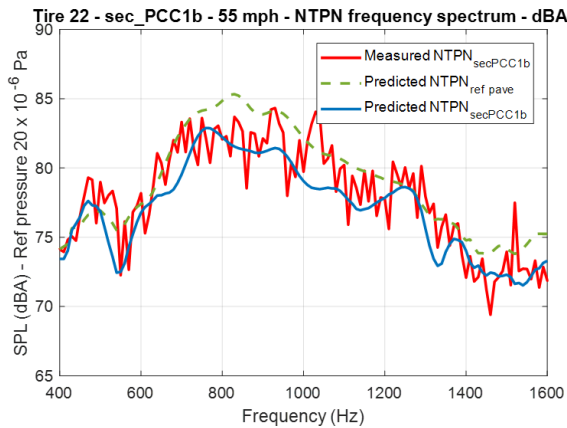
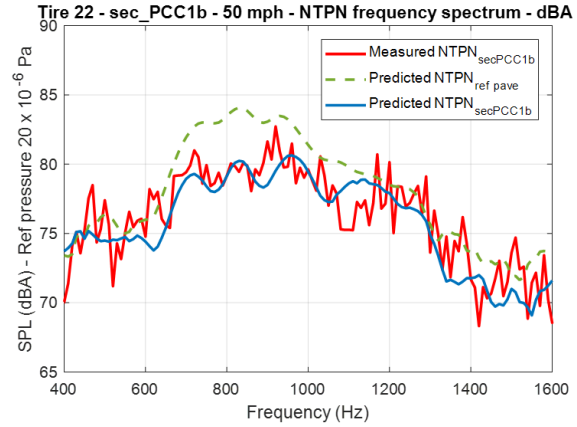


**Figure 68:** NTPN spectrums for Tire 22 on pavement section PCC-1b for vehicle speeds of 50, 55 and 60 mph. Results shown for measured tire noise, predicted NPTN using only tire parameters, and predicted NTPN using both tire and pavement parameters. Frequency resolution: 10 Hz.

The previous figures show the NTPN spectrum correction in the frequency range of interest (400 – 1600 Hz). Additionally, the measured and predicted OASPL are computed for all the tires tested on the SMART road, on the non-porous pavements (12 sections highlighted in Figure 40) and the 4 vehicles speeds tested. Figure 69 shows the comparison between the measured and predicted OASPL. The comparison is made for the model with and without the NTPN pavement scaling module.

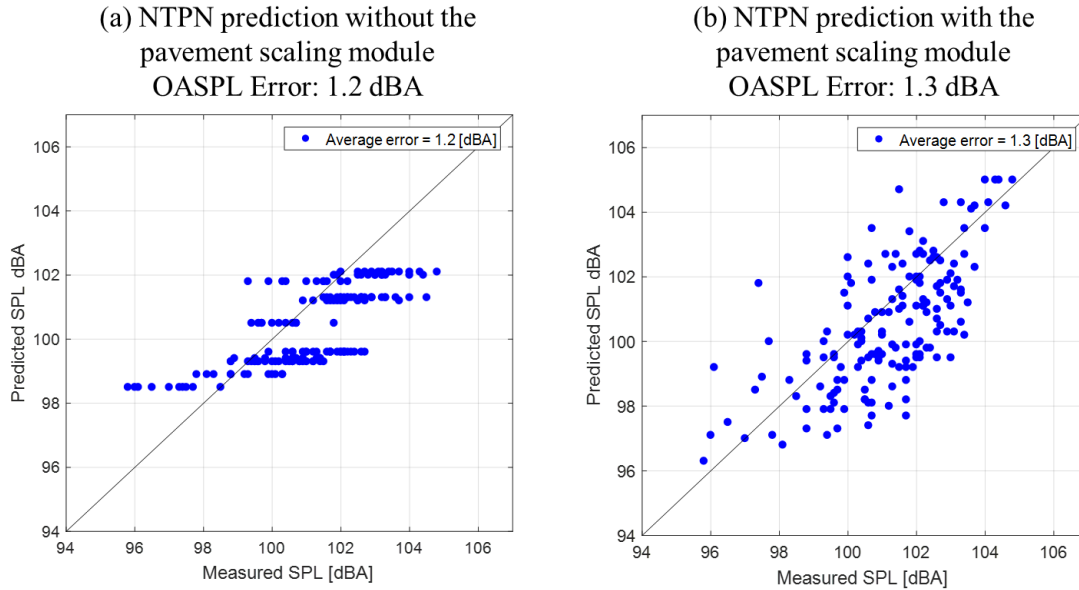


**Figure 69:** Comparison between measured and predicted NTPN overall A-weighted sound pressure level (OASPL) for the tires tested on the SMART road. (a) NTPN predicted using only tire parameters and (b) NTPN predicted using both tire and pavement parameters.

As it was expected, Figure 69(a) clearly shows how the TPIN prediction model without the pavement scaling module predicts one single OASPL value for a tire rolling on different non-porous pavement surfaces. The maximum measured NTPN variation for the same tire rolling on different pavement surfaces is 2.9 dBA. On the other hand, Figure 69(b) shows how the TPIN prediction model with the pavement scaling module is capable to predict in a fairly accurate way different NTPN levels for the same tire rolling on different non-porous pavement surfaces. Strictly speaking, the addition of the NTPN pavement scaling routine increases the OASPL error by 0.1 dBA which is insignificant. Moreover, an overall error of 1.3 dBA is considered to be very good.

The same observations made on the NTPN apply to the TTN results shown in Figure 70. The results for the TTN look similar to the NTPN because the latter is the dominant noise component on the four tires used for validation.

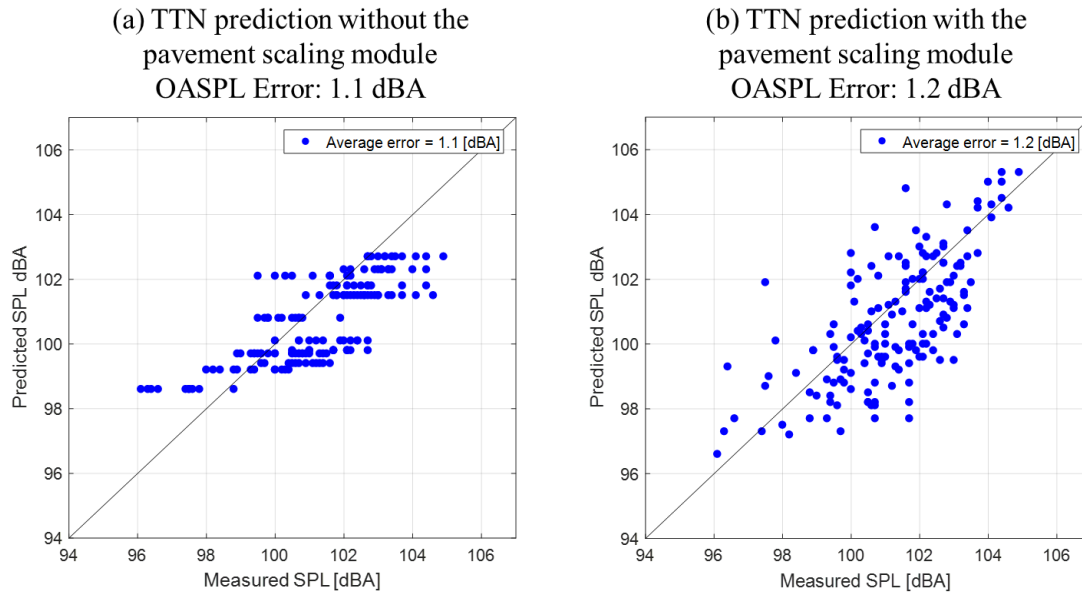


**Figure 70:** Comparison between measured and predicted TTN overall A-weighted sound pressure level (OASPL) for the tires tested on the SMART road. (a) TTN predicted using only tire parameters and (b) TTN predicted using both tire and pavement parameters.

The results shown in Figure 69 and Figure 70 show the final TPIN prediction model capability to predict tire noise for different tires on different non-porous pavement surfaces.

## 5.4 Model specifications and limitations

AMOT specifications are listed in Table 15. They are mainly based on the experimental data used to develop the code (i.e., data used to train both ANNs and find correlations between tire noise and tire and pavement parameters).

| Table 15: AMOT specifications |                        |                                |
|-------------------------------|------------------------|--------------------------------|
| Component                     | Parameter              | Parameter range                |
| Tire                          | Tire width             | 125 mm – 265 mm                |
|                               | Tire outer diameter    | 580 mm – 805 mm                |
|                               | Tread pattern hardness | 56 – 79 (Shore A)              |
|                               | Tread pattern geometry | CTWIST file only               |
| Pavement                      | Type                   | Non-Porous pavement.           |
|                               | Profile                | 1D – scanned pavement profile. |
| Vehicle                       | Speed                  | 40 mph - 70 mph                |

To the best of the author’s knowledge, the following are the AMOT limitations:

1. In general, the accuracy of the model is uncertain for tires outside the tire sizes used to develop the ANNs (see Table 15).
2. AMOT cannot separate tread impact and air pumping contributions to TPN.
3. AMOT reads the tread pattern profile only from files with the scanned CTWIST file format.
4. NTPN is predicted for a reference tire size (i.e., 215/60R16) and later scaled to other tire sizes using a correlation between noise and tire carcass width. This correlation is not very strong (Li, 2017).
5. It only accounts for non-porous pavements. TPIN cannot be predicted for: I) pavements with transversal grooves and II) porous pavements.
6. AMOT only accepts pavement information as one-dimensional profile.
7. AMOT predictions are valid for a tire pressure of 32 psi and load of ~900 lbs. It cannot perform predictions for different tire pressures and loads.
8. AMOT predicts TPIN for new tires. Tire wearing is not accounted for.

## 6 Conclusions and future work

The main conclusions of this work are the following:

1. Through the detailed study of the ANN fundamentals, a specific neuron transfer function configuration to predict only non-negative values was developed. This hybrid configuration was implemented for the unique application of TPIN prediction (i.e., acoustic sound pressure prediction). Moreover, the new ANN configuration was validated and demonstrated to fulfill the requirement of producing only positive results.
2. The tire noise separation procedure was applied for the first time on tire noise data acquired on different pavement surfaces. This allowed to study the two independent components of TPIN (i.e., TPN and NTPN) on multiple pavement surfaces. Such analysis showed that the TPN component of tire noise is independent on the pavement surface profile. The shape and noise levels observed on the TPN spectrums computed on different pavement surfaces are the same. The same analysis showed that the NTPN component of tire noise is dependent on the pavement surface profile. The shape and noise levels observed on the NTPN spectrums varies considerably from one pavement surface to another.
3. The NTPN behavior was investigated for different non-porous pavements present in the VTTI SMART road. It was found that in non-porous pavements surfaces, an increase on the texture levels produces an increase on the NTPN noise levels at low frequencies ( $< 1000$  Hz). On the other hand, the increase in texture levels of non-porous pavement surfaces results in a decrease on the NTPN noise levels at high frequencies ( $> 1000$  Hz).
4. The NTPN spectrums computed on the only porous pavement surface present on the SMART road clearly showed a decrease on the noise levels at high frequencies and an increase on the noise at low frequencies in comparison to the NTPN spectrums obtained for the non-porous pavement surfaces.
5. An approach was successfully developed and incorporated to an existing TPIN prediction model. The final TPIN prediction tool has the capability to predict tire noise

for different non-porous pavement profiles surfaces. This is the first such tool in the open literature.

Possible improvements to be made in future work are:

1. To collect a higher amount of data would improve the ANN training process. Additionally, to test tires outside the range of the parameters specified in Table 15 would reduce the limitations of the TPIN prediction model presented in this thesis.
2. Acquisition of tire noise data for more tires on more different pavement surfaces (non-porous surfaces with different aggregate size, porous pavements, and concrete pavements) would improve the analysis made on Chapter 4. With more tire noise and pavement data, the accuracy of the R function obtained in this work could improve considerably.
3. Measuring the sound absorption coefficient on porous pavement surfaces would provide a better insight on the tire noise produced in this unique pavement surfaces.
4. The NTPN correction module was validated only using noise data of tire sizes similar to the reference tire (215/60R16). The validation was not done on bigger/smaller tire sizes, since there is no data to make such validation. The analysis of tire noise and pavement profile data for different tire sizes tested on different pavement surfaces would help to decide if the NTPN correction performed in this model is correct, or if the adjustment should also take into account the tire size for which the TPIN is meant to be predicted.

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13&rft.pub=Virginia+Tech&rft.advisor=Ng%2C+Wing+Fai&rft.externalDBID=n%2Fa  
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## 8 Appendix A: Non-negative ANN configuration for TPIN prediction using only tire parameters.

### 8.1 Implemented transfer function configurations

Figure 71 shows the three transfer functions studied. Figure 71(a) shows the symmetric sigmoid transfer function (i.e. Hyperbolic tangent function), commonly used for the hidden layer neurons in curve fitting problems. Figure 71(b) shows the pure linear transfer function, implemented in most of the cases on the output layer neurons. A hybrid transfer function combining both symmetric sigmoid and pure linear functions is shown in Figure 71(c).

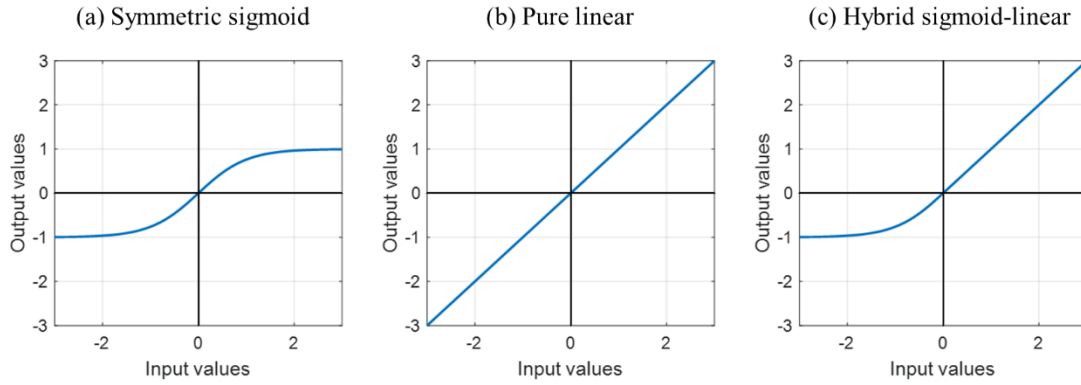


**Figure 71:** ANN output neurons transfer functions studied.

Table 16 shows three different configurations of transfer functions for the hidden and output layer. Configuration 1 is the standard configuration for ANNs in curve fitting tasks. Configuration 2 uses the same transfer function for the hidden layer but replaces the pure linear function on the output layer for a symmetric sigmoid function. Configuration 3 also uses a hyperbolic tangent function for the hidden layer neurons, but for the output layer, the hybrid sigmoid-linear transfer function is implemented. The insight for the customized transfer function is explained in subsection 2.3 along with the ANN model for TPIN prediction.

| Table 16: Investigated ANN transfer functions configurations for TPIN prediction. |                   |                                   |
|-----------------------------------------------------------------------------------|-------------------|-----------------------------------|
|                                                                                   | Hidden layer      | Output layer                      |
| Configuration 1                                                                   | Symmetric sigmoid | Pure linear                       |
| Configuration 2                                                                   | Symmetric sigmoid | Symmetric sigmoid                 |
| Configuration 3                                                                   | Symmetric sigmoid | Hybrid symmetric sigmoid - linear |

## 8.2 ANN for TPIN prediction code

The tire noise separation concept(Feng, 2017) allows us the creation of two separate ANNs (i.e. one for each noise component). From now on we shall refer to them as the ANN<sub>TPN</sub> and the ANN<sub>NTPN</sub> respectively. Figure 72 shows a simplified schematic of the structure of the code. Table 17 shows the inputs and outputs for each one of them. The frequency range of interest (i.e. 400 – 1600 Hz)

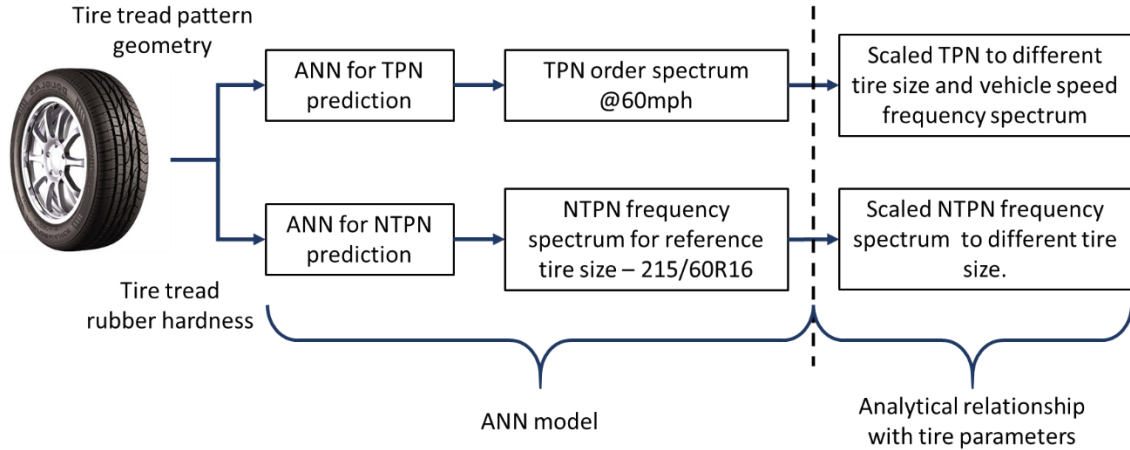


**Figure 72:** TPIN prediction model by (Li, 2017).

Due to the fact that TPN is assumed to be periodic in relation to tire rotation, order power spectrum is preferred instead of the frequency power spectrum. The order can be considered to be a normalized frequency defined as the frequency in Hz divided by rotational speed also in Hz, giving a non-dimensional variable (Li et al., 2016). This approach makes the power spectrum independent of the speed. Moreover, if the speed is known, the process to go from order to frequency power spectrum is straight forward.

| Table 17: Inputs and outputs for each ANN <sub>TPN</sub> and ANN <sub>NTPN</sub> |                         |                                                                                                             |                                                                                       |
|----------------------------------------------------------------------------------|-------------------------|-------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| Layer                                                                            | ANN Tread Pattern Noise |                                                                                                             | ANN Non-Tread Pattern Noise                                                           |
| Input                                                                            | Parameters              | Tread pattern profile spectrum and air volume velocity spectrum (Gaussian curve approximation coefficients) | Parameters Rubber hardness (Shore A) Rotational speed (Hz)                            |
| Output                                                                           | Values                  | Acoustic sound pressure ( $p_{rms}^2$ ) order spectrum                                                      | Values Acoustic sound pressure ( $p_{rms}^2$ ) frequency spectrum (resolution: 10 Hz) |

For the TPIN prediction, the expected output values are  $p_{rms}^2$  (i.e., must be positive). As it was previously mentioned, the data used to train the ANN is normalized to the range  $[-1 \ +1]$  (i.e., -1 corresponds to the lowest  $p_{rms}^2$  value in the training set, while +1 corresponds to the highest).

For the output layer neurons, the use of a pure linear transfer function could result in negative output values (i.e., the lowest possible value to be predicted could be the smaller than the lowest value appearing in the training set). Using a symmetric sigmoid transfer function, no negative outputs are expected. However, the trained ANN has an upper limit for future test cases (i.e., the results shall never be higher than the maximum  $p_{rms}^2$  value present in the training set).

Based on the TPIN problem, the requirements for the transfer function on the output layer are: The lowest value to be predicted should not be less than -1 (i.e., the lowest possible value to be predicted is going to be the minimum value present on the training set.). The transfer function should be able to predict higher values than +1 (i.e., the function should be able to predict higher values than the maximum value present on the training set). In addition, for negative input values, the function should not have a saturated behavior, allowing the ANN to perform better in the problem generalization.

A hybrid transfer function combining both symmetric sigmoid and pure linear functions is proposed and implemented in the output layer to fulfill the previously mentioned requirements.

### 8.3 Non-negative ANN configuration results

In this section, the results for the proposed configurations are presented and discussed. In addition, the comparison between the measured and the predicted Overall A-weighted Sound Pressure Level (i.e., OASPL) for the test tires at all testing velocities are presented

The data acquired at the U.S. Route 460 road (presented in the section 3.2 Experiments) is used to test the new ANN configuration. Table 18 shows the division of the experimental data for each set (i.e. training, validation, and test). An observation to be made is that both ANN test sets involve the same tires i.e., they are not present in the training process of either one of the ANNs.

| Table 18: Tires used for both ANNs training. |                                                                   |                            |                            |
|----------------------------------------------|-------------------------------------------------------------------|----------------------------|----------------------------|
| Set                                          | Training                                                          | Validation                 | Test                       |
| ANN1 for Tread Pattern Noise prediction      |                                                                   |                            |                            |
| Number of tires                              | 13                                                                | 4                          | 8                          |
| Tires                                        | 01 02 03 04 05 06 07 08<br>10 11 13 17 19                         | 12 14 16 20                | 09 15 18 22 23 45<br>49 55 |
| ANN2 for Non Tread Pattern Noise prediction  |                                                                   |                            |                            |
| Number of tires                              | 20                                                                | 9                          | 8                          |
| Tires                                        | 02 03 04 05 07 12 13 14<br>17 19 20 24 25 29 37 39<br>42 53 54 57 | 01 06 08 10 11 16 26 27 43 | 09 15 18 22 23 45<br>49 55 |

#### 8.3.1 TPN results

For practical purposes, the acoustic sound pressure spectrums are presented for the three of the eight test tires detailed in Table 4.

| Table 19: Test tires used to show the acoustic pressure spectrums results. |                  |           |
|----------------------------------------------------------------------------|------------------|-----------|
| Tire number                                                                | Model            | Size      |
| 09                                                                         | Winter tire      | 215/60R16 |
| 15                                                                         | All seasons tire | 215/60R16 |
| 22                                                                         | All seasons tire | 225/60R16 |

For the TPN, the acoustic sound pressure order spectrum comparing all the configurations with the experimental data is shown in Fig. 5. The speed at which the TPN is predicted is 60 mph.

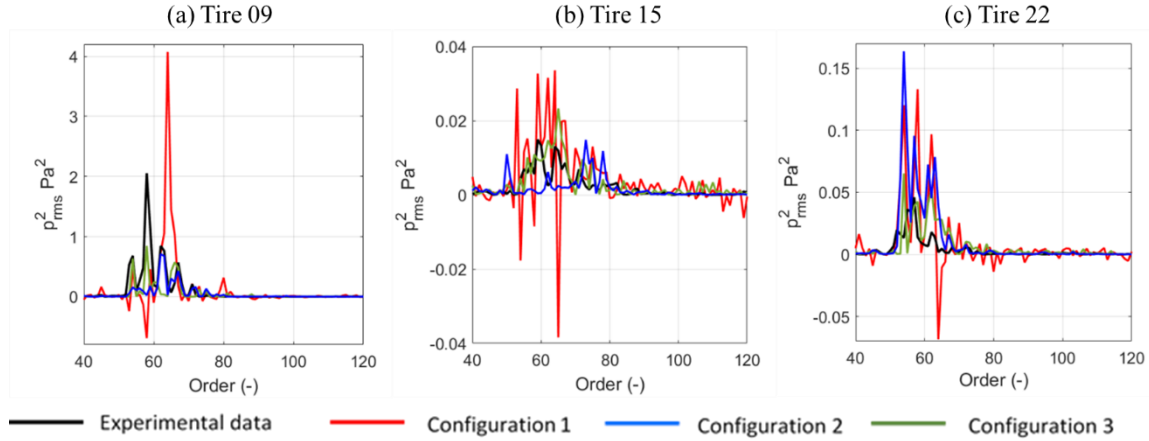


**Figure 73:** TPN acoustic sound pressure order spectrum for different ANN configurations.

As it was expected, configuration 1 predicts negative values of  $p_{rms}^2$  at some orders of the spectrum. On the other hand, the other 2 configurations show no negative output values.

The negative values obtained using configuration 1 are replaced using extrapolation between the immediately prior and immediately subsequent orders with non-negative  $p_{rms}^2$  values. This process artificially adds energy to the system, as shown in Figure 74. In this case the data used corresponds to Tire 09 TPN order spectrum.

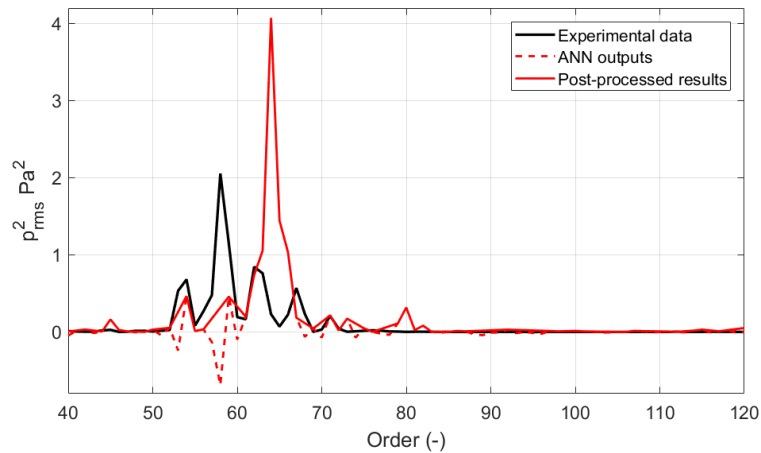


**Figure 74:** Configuration 1 outputs post-processing scheme for Tire 09.

Finally, the TPN OASPL is computed for all tires at the five different speeds. Figure 7 shows the comparison between the three configurations. Configuration 1 shows the highest overall error. Figure 75(a) shows that the results are over-predicted compared to the experimental data which can be attributed to the added energy in the post-processing of the negative values. Configurations 2 and 3 reduce the overall error. In addition, no negative values are predicted.

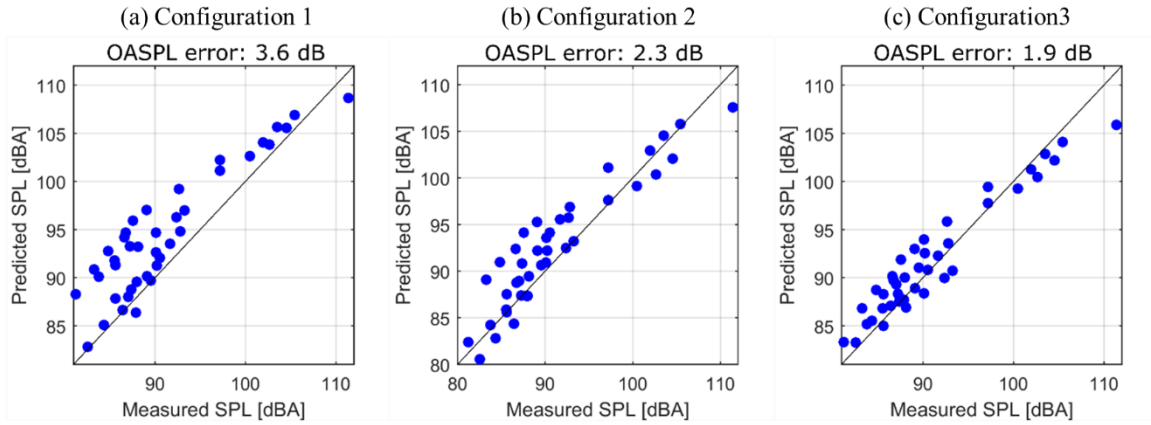


**Figure 75:** Tread Pattern Noise OASPL comparison for test tires at all velocities.

### 8.3.2 NTPN results

For the NTPN, the acoustic sound pressure frequency spectrum is presented in Figure 76 in the same way it was done for TPN. In this case, the predicted values for the three configurations are similar. However, for tires 09 and 15 negative values are predicted at some frequencies of the spectrum. Negative outputs are not as recurrent as they were for  $ANN_{TPN}$  results for configuration 1.

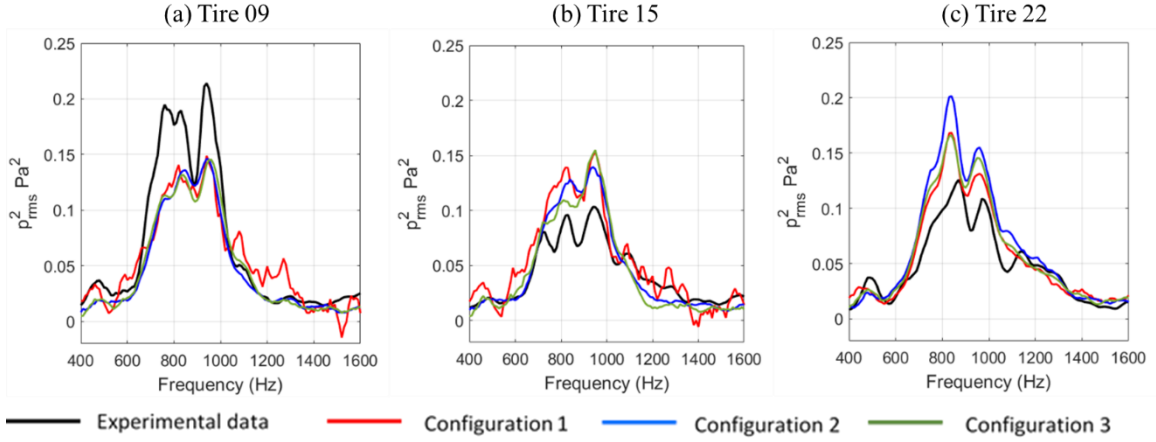


**Figure 76:** NTPN acoustic sound pressure frequency spectrum for different ANN configurations.

Finally, the NTPN OASPL for all test tires at all velocities are compared for all configurations and shown in Figure 77. The improvement, in this case, is smaller than in the ANN<sub>TPN</sub> case. The OASPL error for configuration 1 is 1.2 dBA while for configurations 2 and 3 goes down to 1.0 dBA.

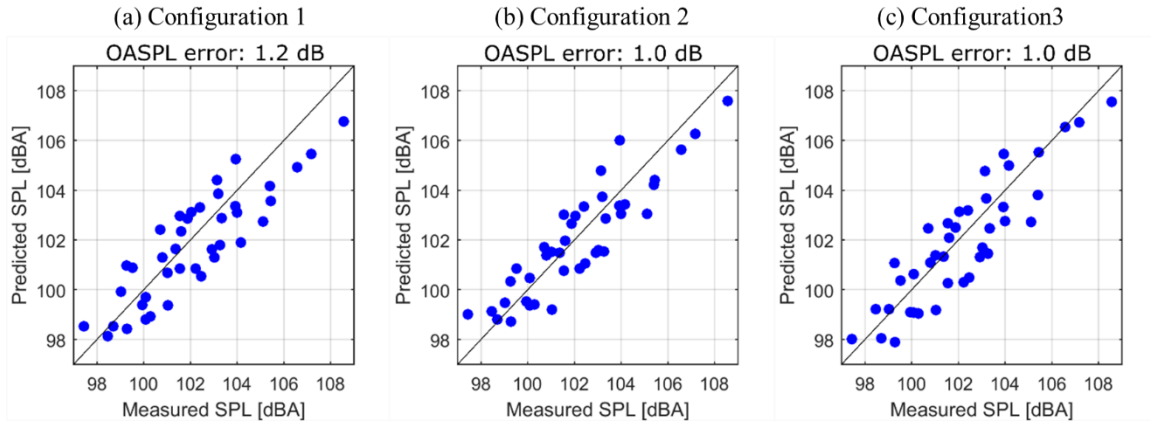


**Figure 77:** Non-Tread Pattern Noise OASPL comparison for test tires at all velocities.

## 8.4 Non-negative ANN configuration results

ANNs can be successfully implemented to predict TPIN using tire parameters. Using standard transfer functions for the hidden and output layers negative output results can be produced. This is physically incorrect due to the nature of the problem (i.e. the outputs are  $p_{rms}^2$ , which is sound pressure and it cannot be negative). In order to obtain positive values,

the negative outputs can be artificially corrected but this adds energy to the system. The final OASPL results for the TPN case are overpredicted by 3.6 dB. For NTPN prediction the error is significantly smaller (1.2 dB).

Furthermore, using a symmetric sigmoid transfer function in the output layer neurons no negative values are predicted. The OASPL prediction improves, obtaining 2.3 dB for TPN and 1.0 for NTPN. Nevertheless, an upper limit for future prediction cases is established during the training process.

A hybrid transfer function combining a symmetric sigmoid function and a pure linear also solves the negative output values. Because of the pure linear behavior for positive values of the function, the trained ANN is not constrained for future test cases, providing the ANN for TPIN with the capability of predicting higher sound pressure values than the highest one present in the training set. The OASPL error for the TPN is 1.9 dB (47.2% less than configuration 1), and for the NTPN is 1.0 dB (16.7 % less than configuration 1).

## 9 Appendix B: SMART road tire noise division information.

### 9.1 Experiments on the SMART road

Figure 78 shows pictures of the vehicle and OBSI setup used to test at the VTTI SMART road.



**Figure 78:** Pictures of tire noise test on the SMART road

Figure 79 shows a simplified schematic of the different pavement sections present in the SMART road (information provided by VTTI). The pavement sections denomination are as follows:

- Regular Surface Mixes (SM) sections are denoted with a letter (except for sections K and L1). They are dense graded mixes with a uniform distribution of aggregate sizes. According to the Virginia Department of Transportation (VDOT), they are commonly used for both structural and functional purposes (exposed to traffic). The number that follows denotes the nominal maximum aggregate size (e.g., SM-4.75, SM-9.0, SM-9.5, SM-12.5, etc.). SM-9.5 are recommended for most final surface applications in the state of Virginia (VDOT).

- Portland Cement Concrete (PCC) pavement surfaces sections are denoted with PCC followed by a number and a letter.
- Section L1 is a Stone Matrix Asphalt (SMA) pavement section. It is a gap graded mix, where the distribution of aggregate sizes is non-uniform.
- Section K is an Open Graded Friction Course (OGFC). They are designed to be water permeable. They have a very low content of fine aggregate material to allow water drainage. It has been reported that the presence of a high percentage of air voids also diminishes TPIN considerably (Sandberg et al., 2002).

The length of the different pavement sections was used in order to crop the tire noise data, and divide it into the different pavement sections. In the following, the tire noise division process is explained in detail.

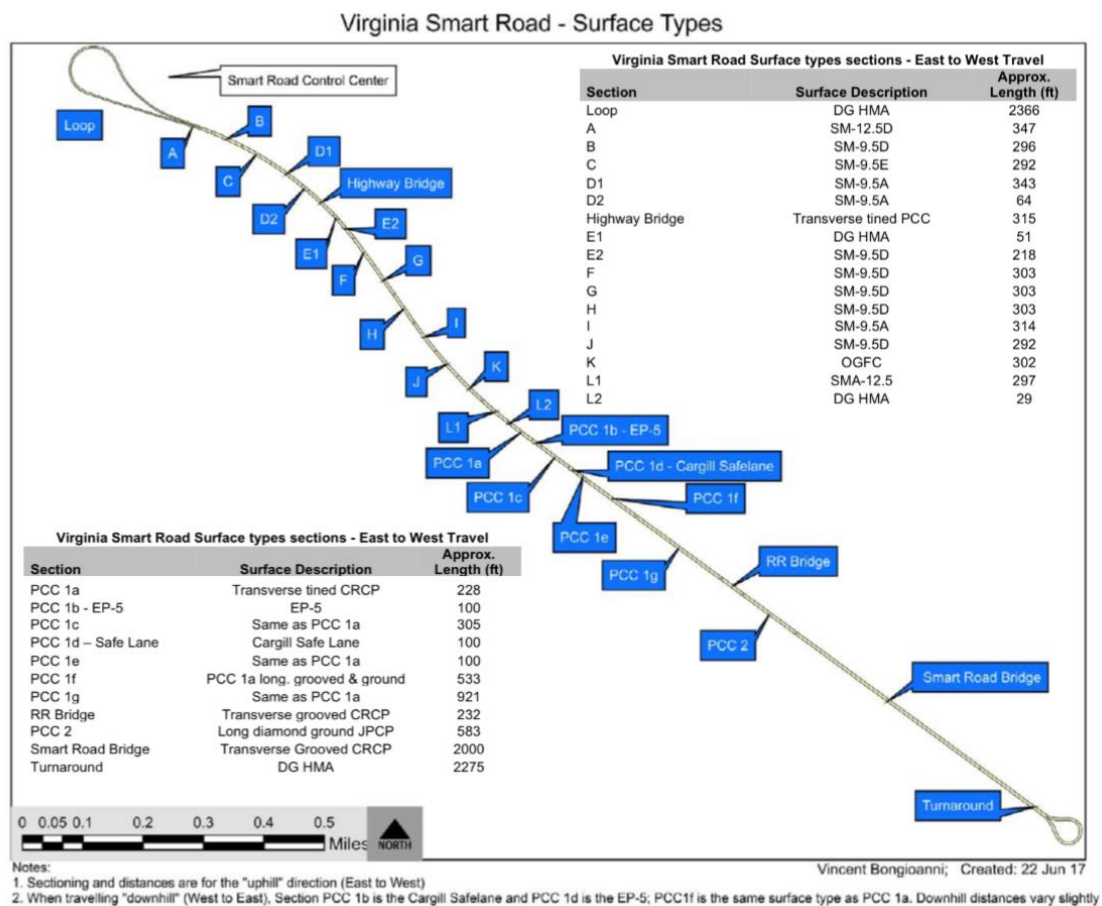


**Figure 79: SMART road pavement sections.**

First, the number of sample points for each section ( $Nb_{samp}$ ) is computed using the distance of each pavement section ( $d_s$ , information provided by VTTI), along with the vehicle speed ( $V_{speed}$ ) and the microphones sampling frequency ( $f_{samp} = 25600$  Hz).

$$Nb_{samp} = \frac{d_s}{V_{speed}} \cdot f_{samp} \quad (9.1)$$

Figure 80 shows the real pavement section lengths superposed to the tire noise spectrogram. This corroborates the proposed approach to divide the tire noise for the different SMART road sections. The SMART road bridge section is used as an example. It represents the longest section of the track with transversal grooves. The tone due to the presence of the grooves is clear on the total noise spectrogram.

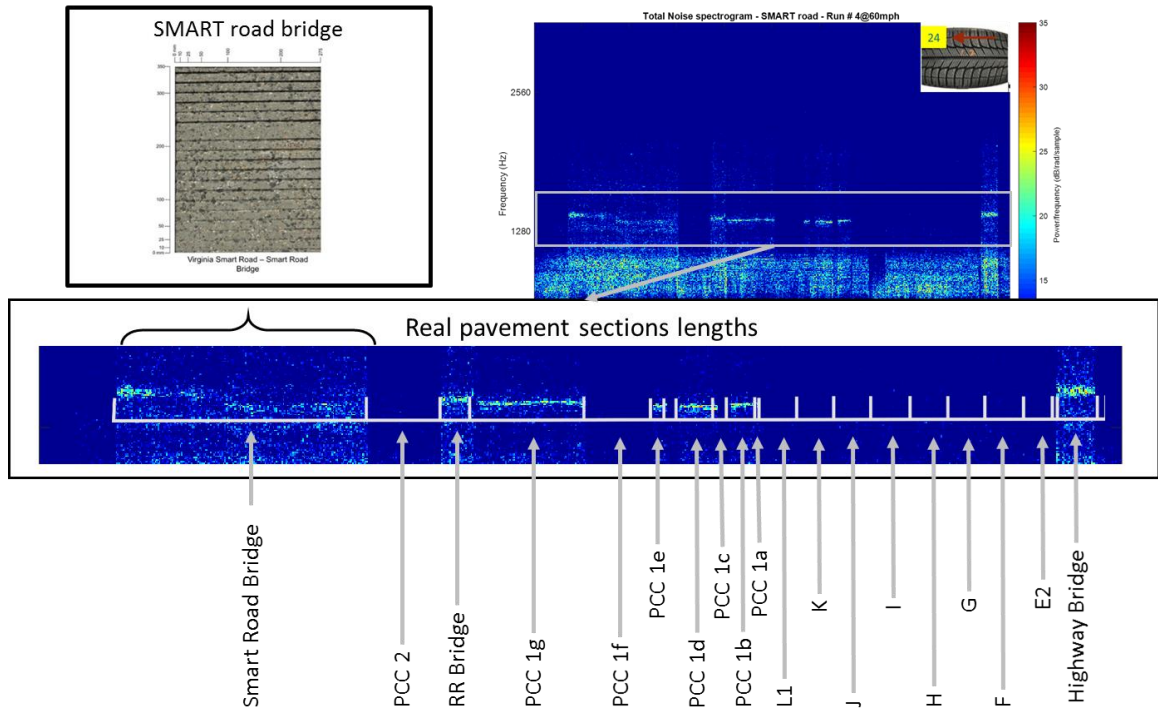


**Figure 80:** Different Pavement sections identification in the SMART road tire noise.

The process to divide the tire noise into the different pavement sections was applied to all the tire noise data collected on the SMART road. An example of the tire noise (TPN, NTPN and TTN) spectrums and the pavement profile spectrum is shown in Figure 28.

.

## 10 Appendix C: U.S. Route 460 pavement distress

A specific place on the eastbound test section was identified, where a clear tone appeared on the tire noise data. Li was able to visually identify the presence of pavement distress on the road (see Figure 82). Tire noise for normal sections of the U.S. Route 460 road and the corrugated pavement section were compared. The comparison was made for Tire 20 (SRTT tire) at a vehicle speed of 60 mph, and it is shown in Figure 81.

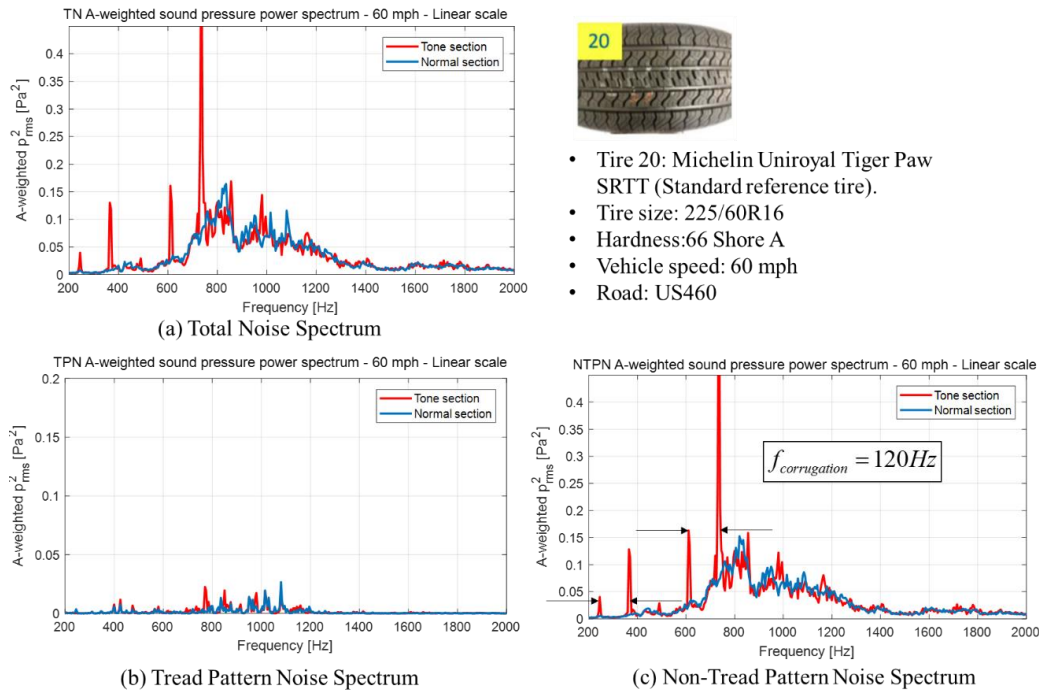


**Figure 81:** (a) Total Noise spectrum, (b) Tread Pattern Noise spectrum, and (c) Non-Tread Pattern Noise spectrum. Frequency resolution: 5 Hz.

The tones can be clearly seen on the TN and NTPN spectrums. However, they are not visible on the TPN spectrum. Once again, this becomes a strong evidence to prove that the NTPN is the tire noise component strongly related to pavement surface features. It is observed on the NTPN that the frequency between peaks ( $f_{corrugation}$ ) is approximately 120 Hz. Using this information, along with the tire circumference and the vehicle speed at which the noise was collected (same procedure implemented with pavement surfaces with transversal grooves), the fundamental wavelength of the corrugation can be computed as

$$\lambda_{\text{corrugation}} = \frac{f_{\text{rot-tire}} \cdot l_{\text{tire}}}{f_{\text{corrugation}}} = \frac{12.8\text{Hz} \cdot 2.12\text{m}}{120\text{Hz}} \cong 0.23\text{m} \quad (10.1)$$

where  $f_{\text{rot-tire}}$  is tire rotation frequency in Hz (in this case for a vehicle speed of 60 mph),  $l_{\text{tire}}$  is the circumference of the tire in meters, and  $f_{\text{corrugation}}$  is the frequency between tones observed on the NTPN in Hz.

Additionally, the pavement profile data was used to continue investigating this particular case. The pavement profile spectrum was computed for different sections of the US460 road. It was found that a tone appeared on the pavement profile spectrum for the same place of the test section where this behavior was observed on the tire noise. The pavement profile spectrums for a normal section, and a corrugated section are compared in Figure 82.

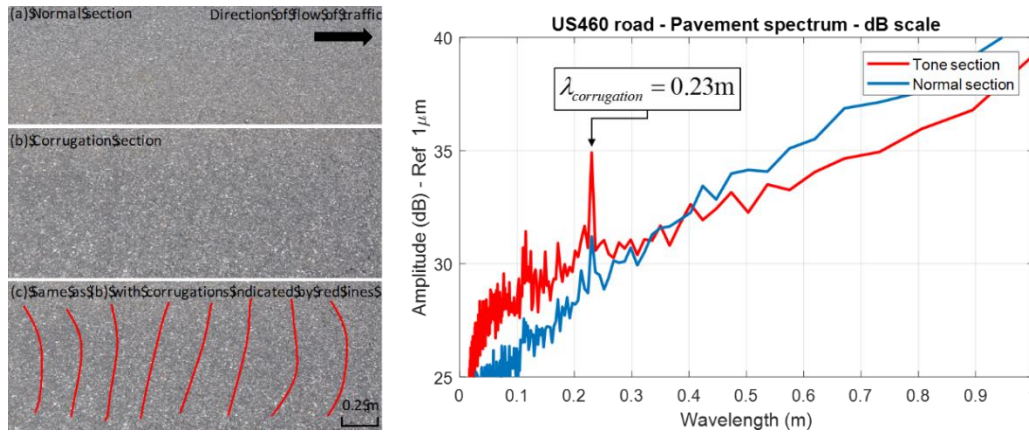


**Figure 82:** (left) Pictures of the US460, normal section and corrugated section, (right) Pavement profile wavelength spectrum.

This case presents similarities to the transversal grooves sections studied in subsection 3.4.2. The fundamental corrugation wavelength computed using the NTPN data (frequency between tones on the NTPN) matches the dominant wavelength found when computing the pavement profile wavelength spectrum.

## **11 Appendix D: Model validation results using only tire parameters**

The key to the development of the AMOT model is the two ANN sub-models to predict the tread pattern noise on one side and the non-tread pattern noise on the other side. The tire samples used to develop both ANNs are shown in Table 14. Although the train/validation sets for the ANN meant to predict the TPN are different from the ANN for NTPN prediction, the test set for both ANNs is the same. Therefore, they can be used to evaluate the accuracy of the model using only tire parameters.

The results for the tires in the test set exclusively used for the final validation of AMOT are presented in the following. Only the narrowband spectrum is presented; the 1/3 octave band spectrum shows the similar trends.

The results for Tire 09 are demonstrated in Figure 83. Good agreement between the measurement and prediction is shown. It is noted that, in Figure 83b, the tread pattern noise results for Tire 09 are good for 60 mph. However, the tread pattern noise results for lower speed are slightly over-predicted, and the tread pattern noise results for higher speed are under-predicted. This is because the real speed exponent for Tire 09 is about 7, but AMOT uses a speed exponent of 4 to scale results from 60 mph to other speeds. Figure 83d-f shows that the non-tread pattern noise is somewhat under-predicted, which ends up with an under prediction for the total tire noise at the higher speeds.

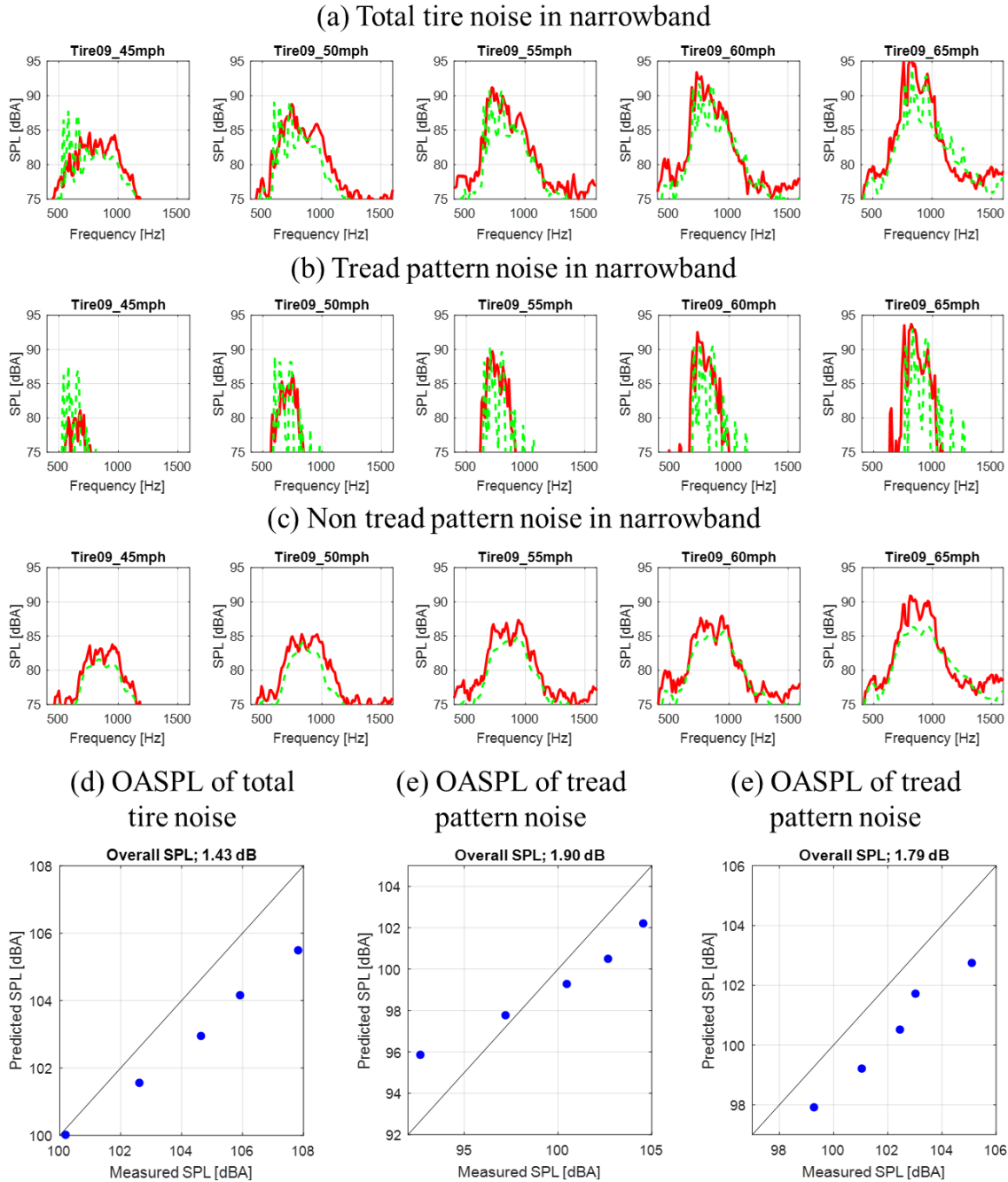


**Figure 83:** Results of AMOT for Tire 09 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 15 are demonstrated in Figure 84. Good agreement between the measurement and prediction is shown. For this tire, the tread pattern noise is marginal compared to the non-tread pattern noise.

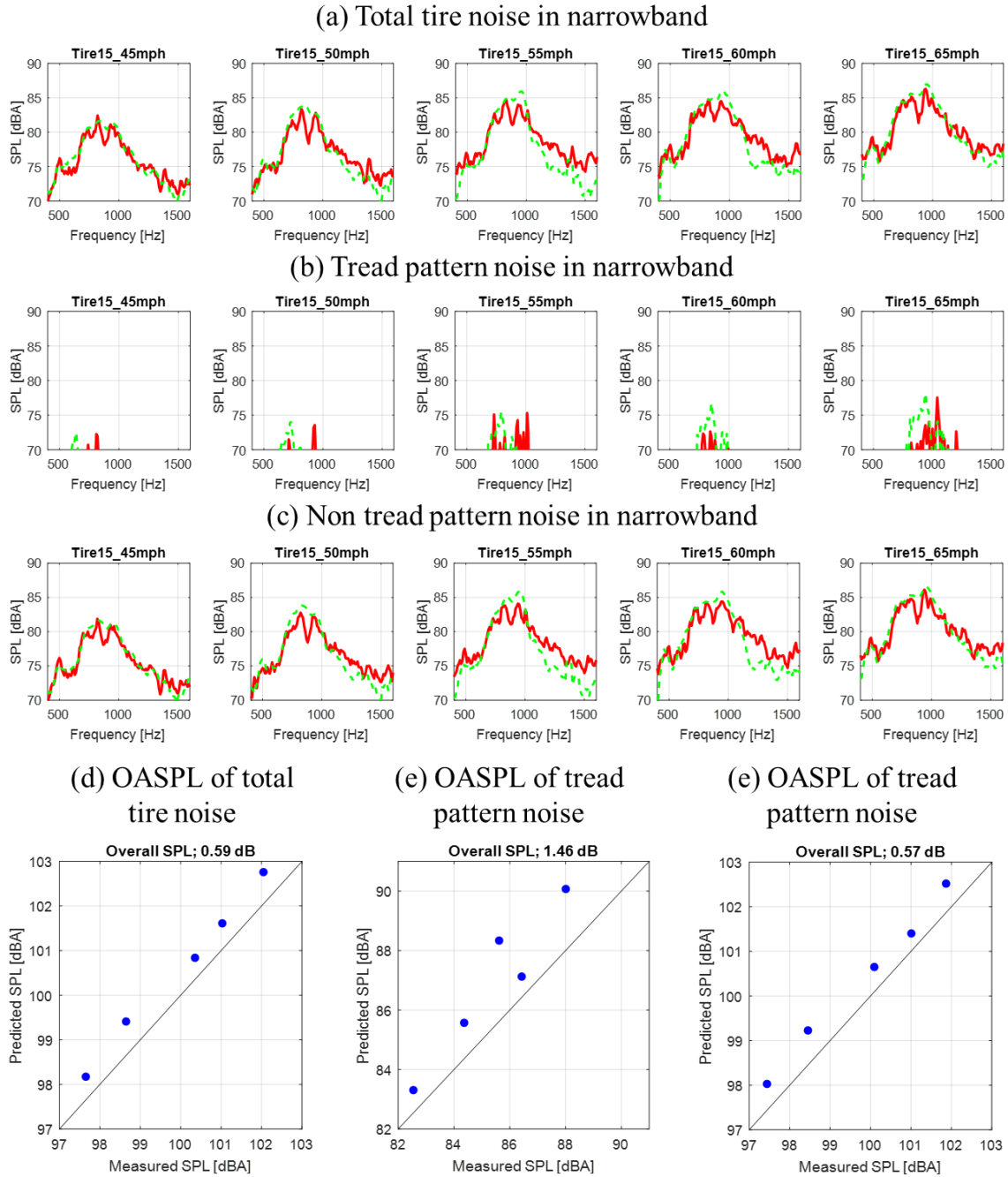


**Figure 84:** Results of AMOT for Tire 15 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 18 are demonstrated in Figure 85. Good agreement between the measurement and prediction is shown. The non-tread pattern noise is a little bit under-predicted.

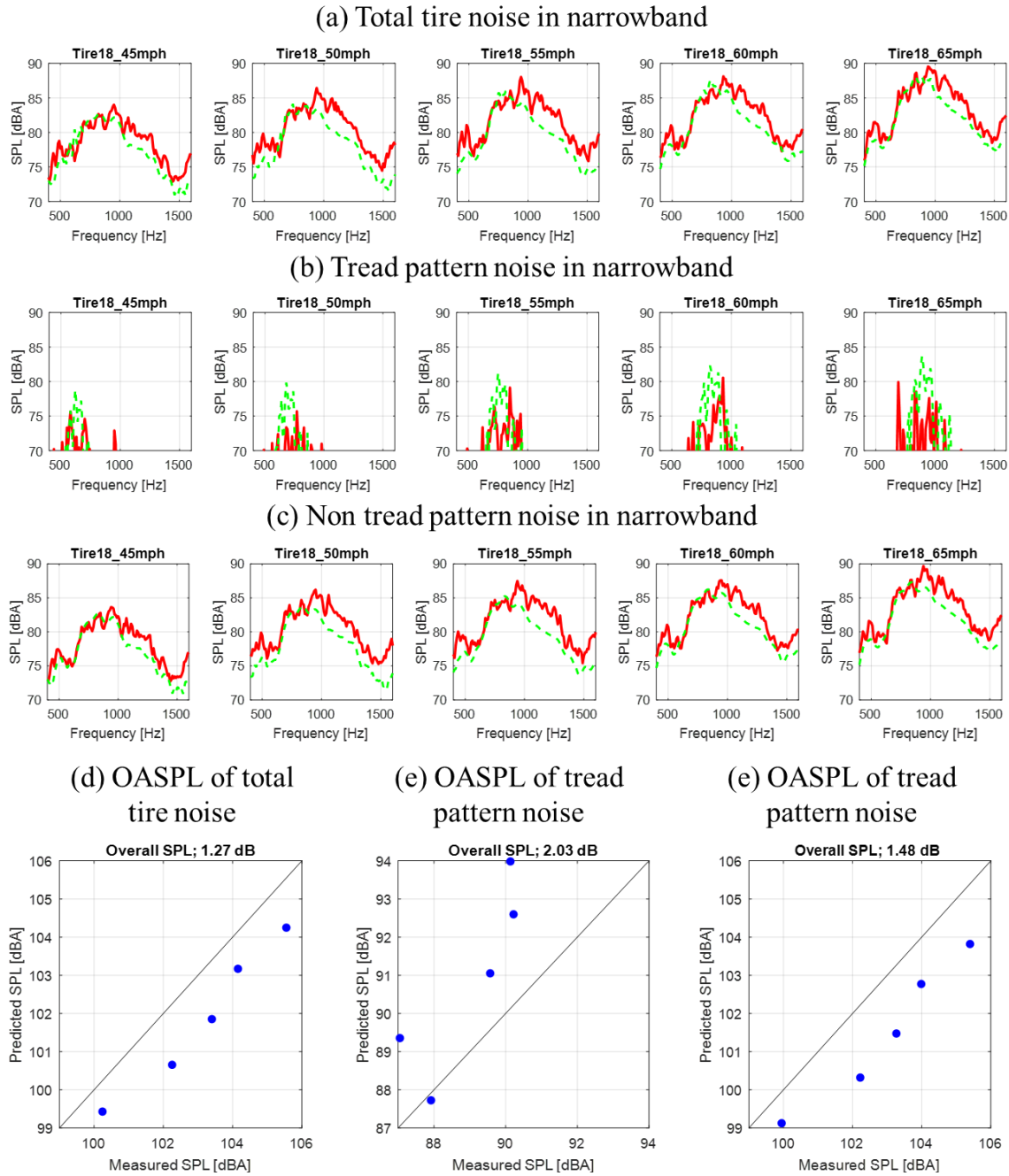


**Figure 85:** Results of AMOT for Tire 18 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 22 are demonstrated in Figure 86. The tread pattern noise is over-predicted by about 3.9 dB for all the speeds due to the over-prediction at 60 mph. However, since the tread pattern noise is very small compared to the non-tread pattern noise, the prediction for the total tire noise is still not bad ( $\sim 0.8$  dB error).

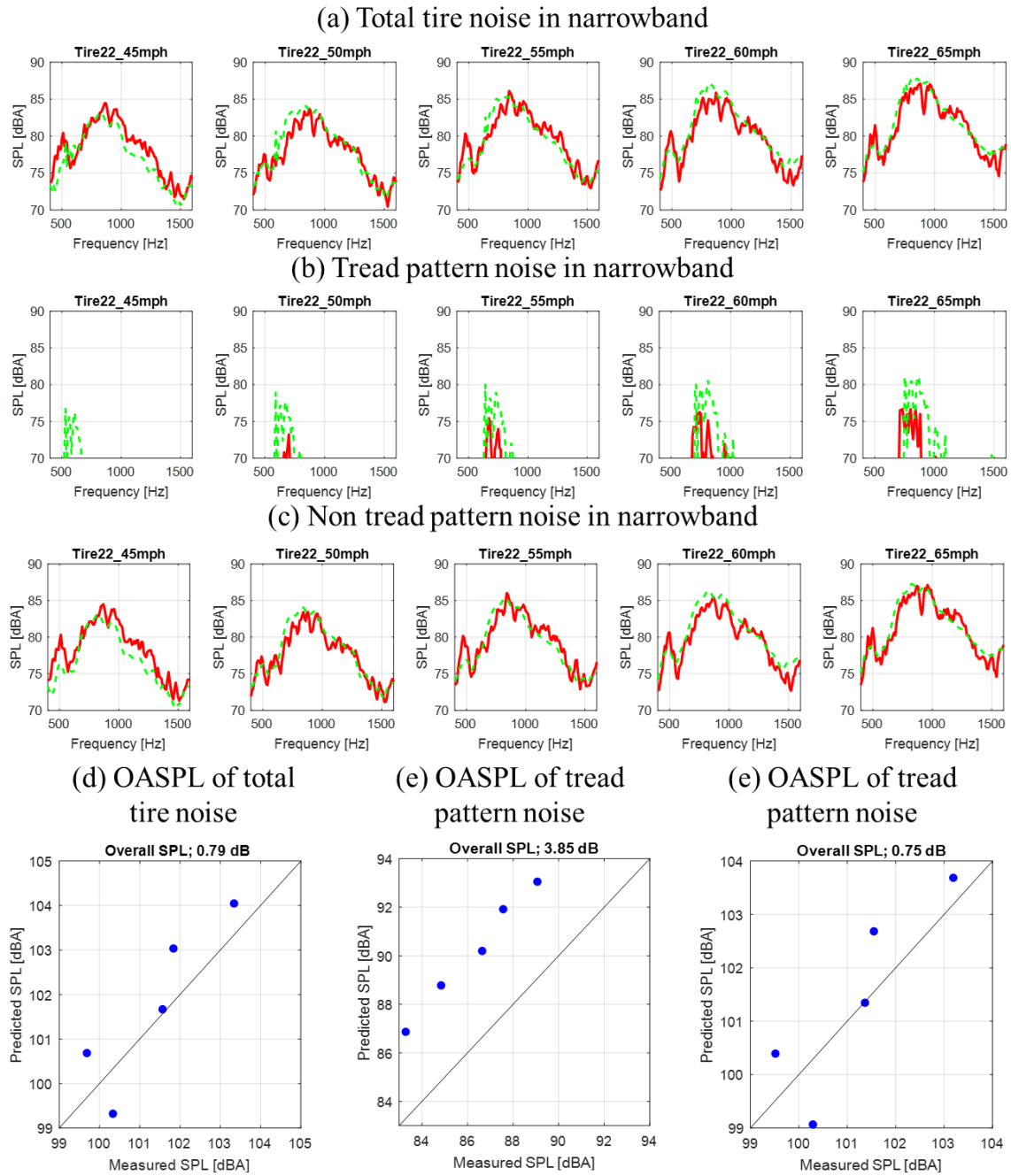


**Figure 86:** Results of AMOT for Tire 22 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 23 are demonstrated in Figure 87. The tread pattern noise is over-predicted by about 1.7 dB for all the speeds due to the over-prediction at 60 mph. However, since the tread pattern noise is very small compared to the non-tread pattern noise that is also under-predicted by about 1.1 dB, the prediction for the total tire noise is still acceptable.

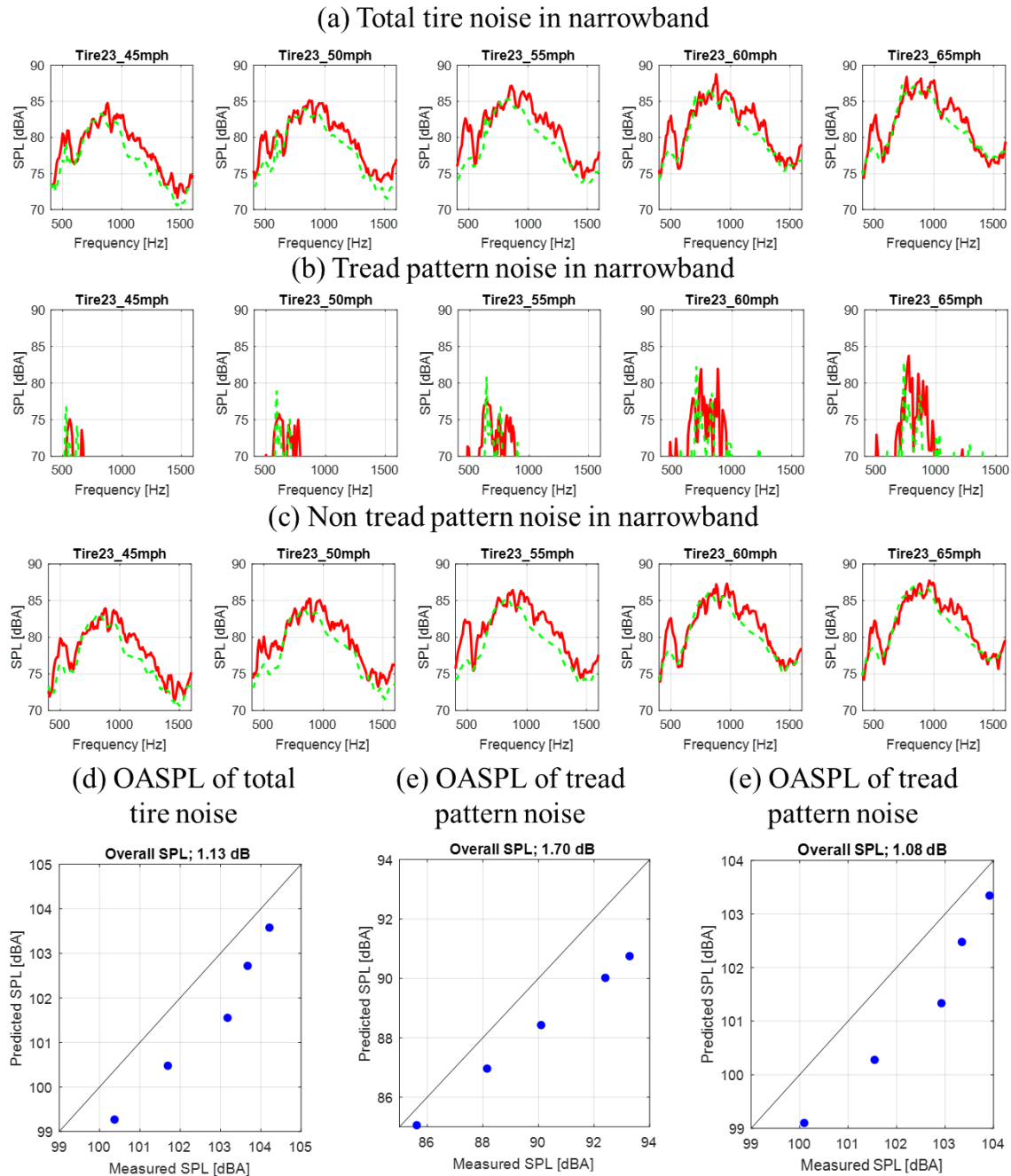


**Figure 87:** Results of AMOT for Tire 23 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 45 are demonstrated in Figure 88. The tread pattern noise is over-predicted by about 1.8 dB for all the speeds due to the over-prediction at 60 mph. However, since the tread pattern noise is insignificant compared to the non-tread pattern noise, the prediction for the total tire noise is good enough ( $\sim 1.6$  dB error).

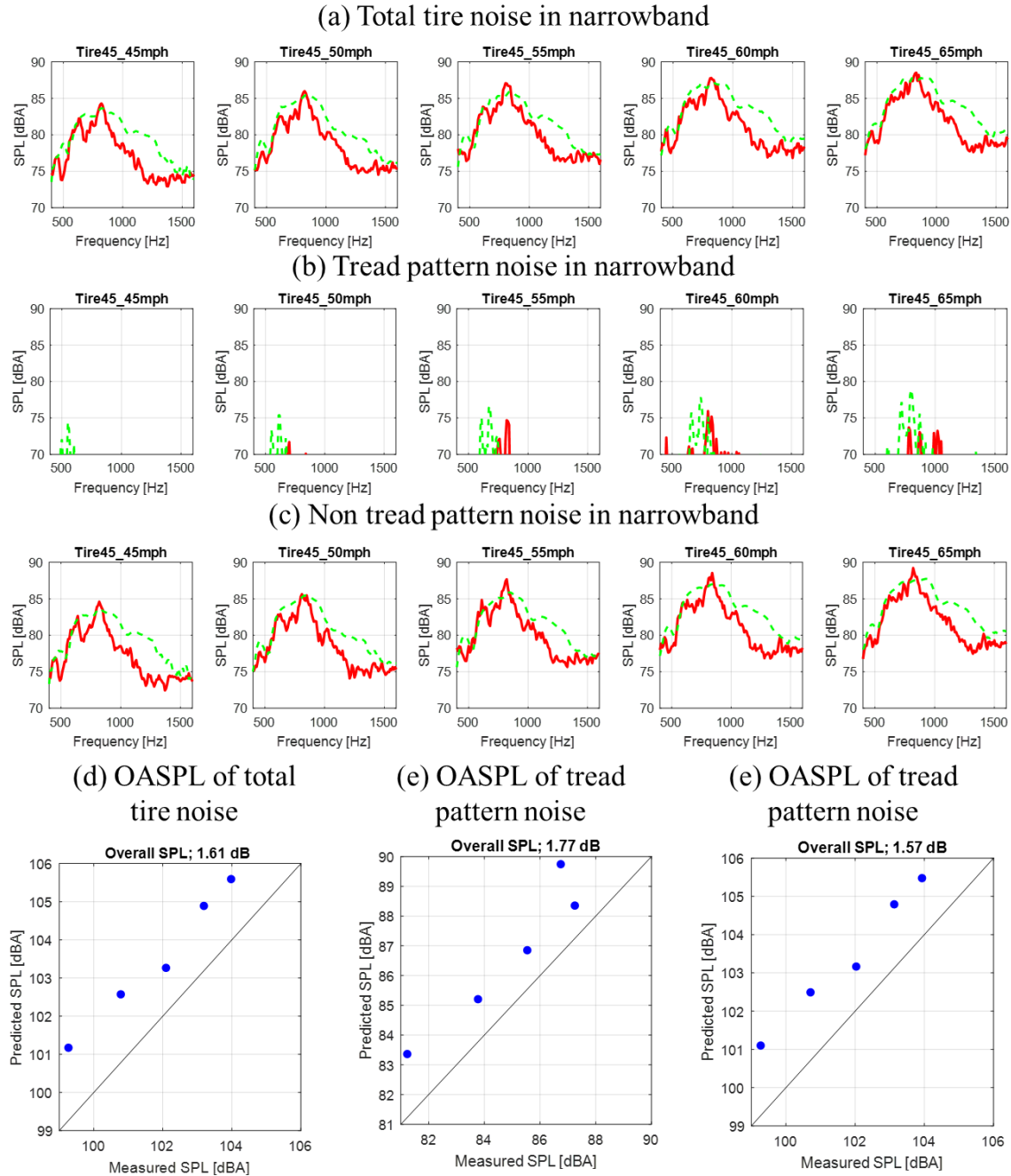


**Figure 88:** Results of AMOT for Tire 45 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 49 are demonstrated in Figure 89. Good agreement between the measurement and prediction is shown. It is important to note that, the tread pattern noise for this tire is very large, and the AMOT successfully predicts it, including the spectral amplitude and peak location.

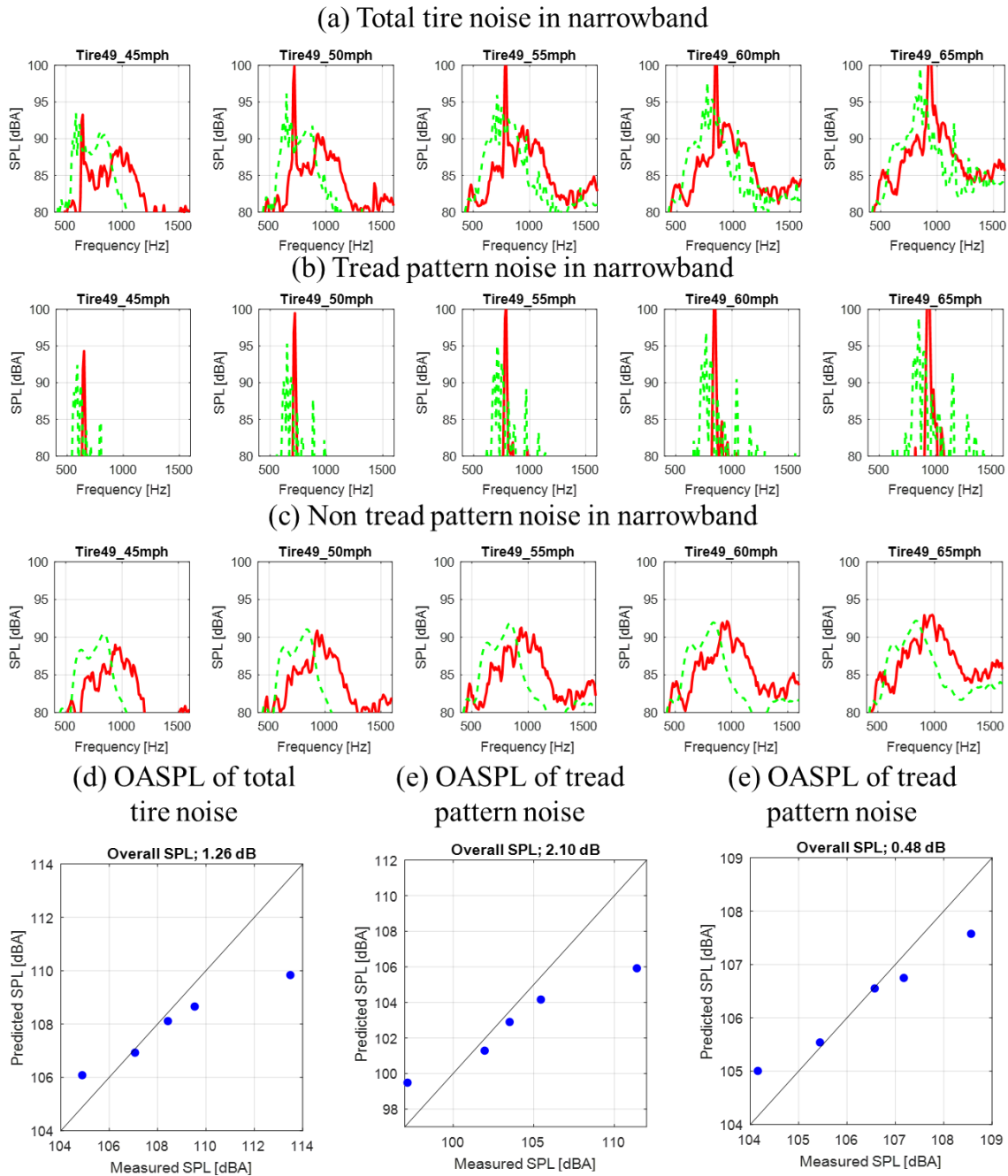


**Figure 89:** Results of AMOT for Tire 49 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).

The results for Tire 55 are demonstrated in Figure 90. Good agreement between the measurement and prediction is shown.

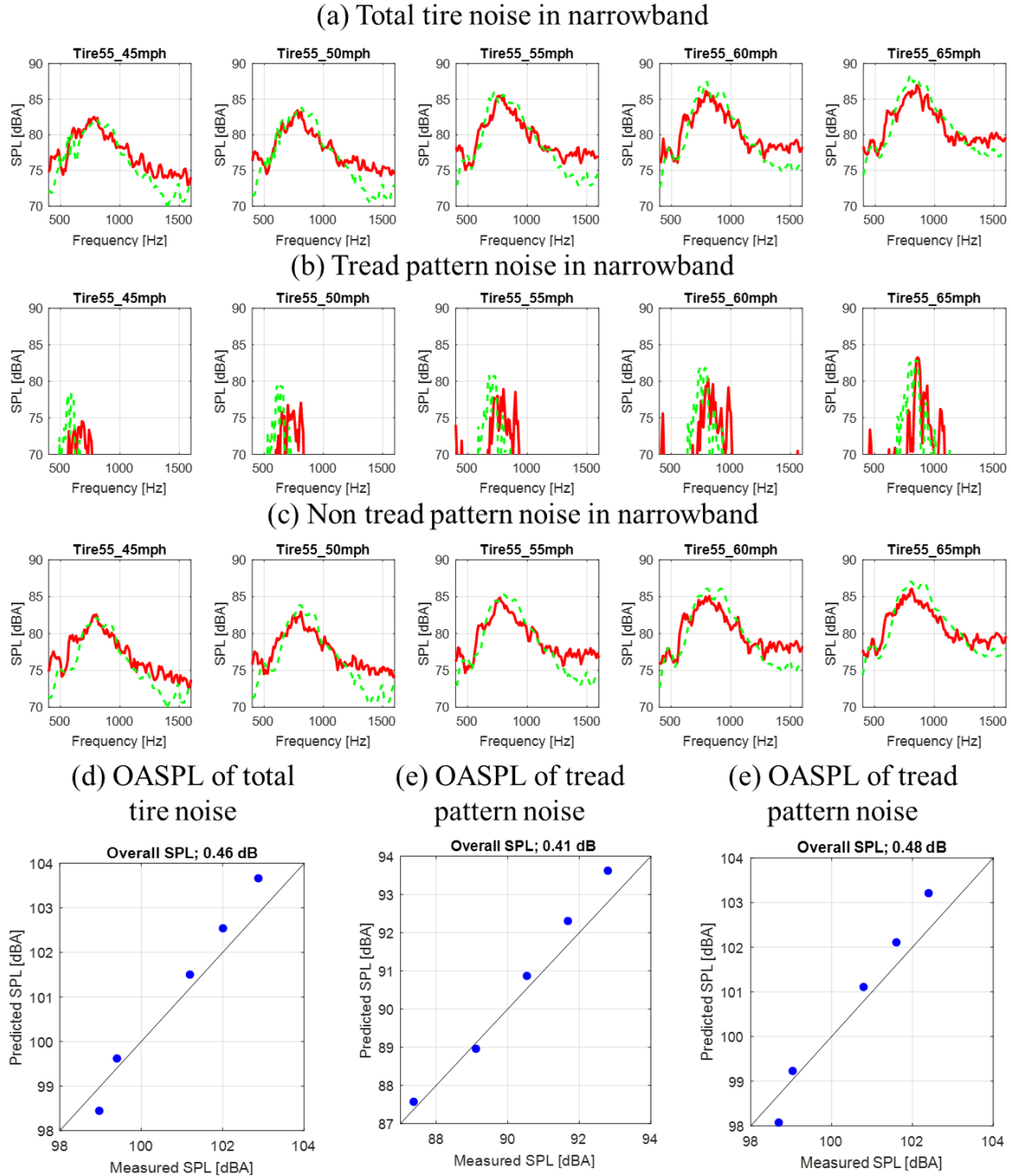


**Figure 90:** Results of AMOT for Tire 55 (in a-c, red denotes measured, green denotes predicted; in d-f, the value above the plot is the average dB error).