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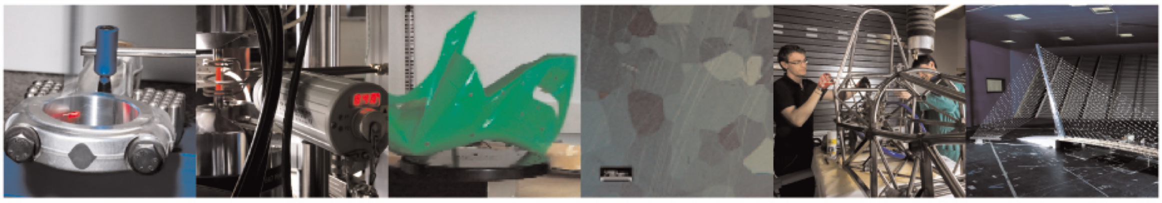

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Processing of tyre data for rolling noise prediction through a statistical modelling approach

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Abstract

Nowadays, tyre/road noise represents one of the main sources of environmental pollution. For this reason, tyre/road noise models are fundamental to support the design of more silent products. In this paper, a statistical modelling approach is discussed, with particular focus on the identification and processing of noise-related tyre/road parameters. At first, the workflow for the development of a statistical tyre/road noise model is described. This strategy is then applied to the prediction of sound intensity levels of indoor tests performed on drum at different rolling speeds. The measurement of input and output data and their processing are discussed and applied to the define a suitable database. The proposed approach is then tested with a neural network. The results show the potential of the presented methodology in terms of selection of descriptive parameters and features' extraction procedure.

Keywords: tyre/road noise (TRN), noise-related parameters, tread pattern, neural network

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1 Introduction

Noise is the second cause of pollution in Western Europe. Among the main sources, tyre/road noise (TRN) is the predominant one [1, 2]. To limit this phenomenon, regulations have been introduced and the automotive industry is investing considerable resources in the development of methodologies for the estimation of TRN. Indeed, predictive models would be beneficial in early stages of product development, especially for tyre manufacturers.

Several TRN models have been developed which can be categorized as deterministic, statistical or hybrid models [3]. On the one hand, deterministic models are based on the knowledge of the physical phenomena that take place during tyre operation and are typically developed either through an analytical approach or by means of numerical techniques, such as finite element method, boundary element method or computational fluid dynamics. On the other hand, statistical models are semi-empirical and based on the correlation between measured tyre noise data and associated tyre/road parameters. Since statistical models are data-driven, often a data processing strategy for evaluating the most correlated features is essential to increase the model accuracy. Comparing the statistical and the deterministic approaches, the latter are typically useful in improving the understanding of the mechanisms that generate and amplify tyre noise, whereas statistical models can provide more accurate quantitative predictions, but no physical interpretation of the results is given. For these reasons, hybrid models could be also defined to benefit of the advantages of the two strategies by combining statistical and deterministic approaches.

Nowadays, the modelling of TRN can be considered as an open research field and a complete understating has not been reached yet due to the complexity of the involved generation and amplification mechanisms [4]. Nonetheless, many research activities proved that TRN is strictly related to the tread pattern drawing and the characteristics of footprint region [5]. Therefore, accurate TRN models should take into account these parameters with a sufficient level of detail. In this context, taking into account the difficulties related to physical modelling, the statistical approach can represent a valid solution to obtain quantitative TRN predictions.

Regarding statistical models, previous studies focussed on the prediction of the tread pattern noise. Tread pattern noise can be isolated with an order tracking analysis, by processing the acoustic measurement considering the signal of a tachometer mounted on the tyre during the tests. In [6], the separation of the tread pattern noise from the TRN measured with an On-Board Sound Intensity (OBSI) approach is discussed. Neglecting the non-periodic part of TRN, Li et al. [7] investigated the correlation between tread pattern noise and tread profile and air volume velocity spectra in the 20-2000 Hz frequency range using Artificial Neural Network (ANN). In this work, the two spectra were processed with Gaussian curve fitting procedure, and Gaussian parameters were used as inputs to the Artificial Neural Network (ANN). In [8], Mohammadi et al. used a different approach, where the tread pattern data were not included as input parameters but the tyre structure characteristics and operative conditions (such as the width, the aspect ratio, the tread impact pressure, tyre velocity etc.) were considered. Meanwhile, tests were executed according to the ISO 13325 coast-by methodology at eight different speeds, and no separation of the tread pattern noise was performed. Differently, Che et al. [9] performed TRN measurement by laboratory drum method and defined a different ANN that was trained using genetic algorithm. In this case, no tread profile spectra were considered as input parameter. Furthermore, Convolutional Neural Network (CNN) is a valid alternative to ANN for the prediction of TRN. In [10], a comparison between these approaches is carried out, aiming at predicting the SPLs of the tread pattern noise measured in a semi-anechoic chamber. It is worth mentioning that the CNN's inputs were directly the images of the tread pattern and no processing was required, whereas a processing similar to [7] was applied to the inputs of the ANN to carry out a comparative analysis.

In this paper, the processing of tyre data for the prediction of TRN through a statistical approach is discussed. At first, a general workflow for the development of tyre/road noise statistical models is presented. Then, a specific test case is considered, based on indoor sound intensity measurements of tyres rolling on drum (laboratory drum approach). With respect to other research activities that also focussed on the prediction of TRN in outdoor conditions, in this work the indoor condition was preferred in order to investigate the effect of tyre parameters only, neglecting environmental effects. This work also benefitted of a large database with respect to previous activities. Indeed, a set of 83 tyres was tested at three different rolling speeds. Moreover, aiming at evaluating the very same sound intensity levels acquired during the tests, thus the total TRN, no tread pattern noise separation was applied. During the experimental campaign, noise-related tyre/road parameters were identified; they were classified into four different categories and measured. These parameters refer to tyre structure, footprint dimensions, tread pattern and tyre operative conditions during the tests. Subsequently, the data of both TRN noise measurements and tyre/road parameters was processed to extract relevant indicators and noise-related features. The analysis focussed on the 200 Hz - 4 kHz frequency range, and a total of 24 input and 14 output parameters corresponding to sound intensity levels evaluated across 14 one-third octave bands were evaluated from the measured data. The focus of this work is the data processing and the assessment of the potential of the approach, still relying on a simple neural network. Nonetheless, the obtained approach can be used to build or enrich databases to train a generic statistical model (ANN, CNN, etc.).

This paper is structured as follows. In Section 2, the typical structure of a statistical model is presented in terms of inputs and outputs. Subsequently, in Section 3, the TRN measurements and the evaluation of noise-related parameters is discussed. In Section 4, the processing of the outputs and the inputs is described. In Section 5, an ANN is created to relate the input parameters and the noise sound intensity levels. Eventually, Section 6 discusses the results and Section 7 draws the conclusions.

2 Methodology

Figure 1 shows the workflow for the development of a tyre/road noise statistical model (for each stage, reference is made to the section of this paper in which the related contents are discussed). Three stages can be identified: data collection, data processing and statistical model definition. Starting from the bottom of the diagram, the statistical model is represented as a black box that associates a set of outputs with certain inputs. For the statistical model to predict the tyre rolling noise, the inputs come from a selection of tyre parameters with or without a data processing, and the outputs should be tyre noise indicators corresponding to a specific measurement technique and a given quantification.

The outputs determine the target of the statistical model. The TRN levels can be different when different measurement techniques are used. Therefore, if a statistical model is trained on data measured through a certain technique, the model is specific to this technique. In this work, , the statistical model is aimed at predicting the rolling noise measured in a semi-anechoic chamber according to the laboratory drum method,. More details are specified in Section 3.1 and in Section 4.1. However, many other methods can be adopted to measure tyre noise (as summarized by Li in [11]) and some of them are listed in Figure 1.

The next step of the workflow is the evaluation of the input parameters. In principle, there could be many tyre/road parameters associated with the rolling noise. Figure 1 presents some of these parameters and divides them into four categories, i.e., tyre structure parameters, footprint parameters, tread pattern parameters and operating parameters. The selection of the inputs relies on the significance of the parameter to the tyre noise and its correlation with the output parameters and on the possibility of evaluating these inputs for each item in the dataset.

Once TRN measurements and noise/related input parameters have been measured, a processing stage is required. From the point of view of the output data, this stage is needed to extract indicators that are useful to predict the tyre acoustic performances in an effective way. Regarding input parameters, a processing stage is required for the extraction of meaningful tyre features to be related to the target outputs and to reduce the number of input parameters. Moreover, it is important defining a feasible number of input and output parameters based on data availability, giving priority to the features that are mostly related to the target outputs.

Finally, considering that the data collection and processing stage are completed, the workflow in Figure 1 focuses on the statistical model itself. This stage includes the selection of an appropriate modelling approach, the determination of a good model structure and the training process that uses the prepared datasets of inputs and target outputs.

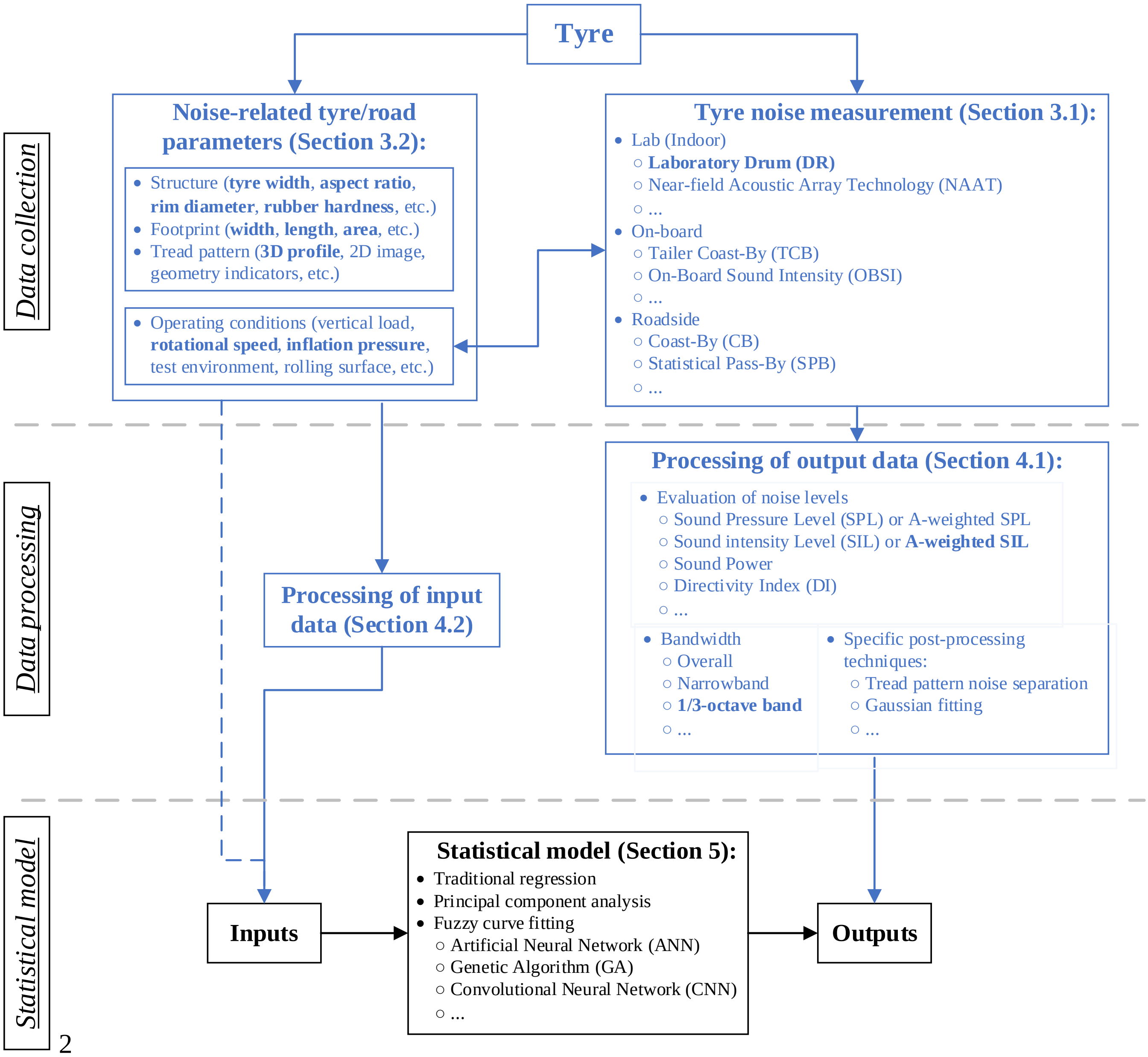


Figure 1 Workflow and methodology for the development of a tyre/road noise statistical model.

3 Data collection

In this section, the first stage of the workflow represented in Figure 1 is discussed, specifically focussing on the description of the experimental tests carried out in the framework of this work. In this case, data of 83 tyres rolling at different speeds are collected for the prediction of TRN sound intensity levels acquired during indoor tests. Four different typologies of noise-related tyre/road parameters are identified and measured. Particular attention is devoted to the description of the tread pattern geometry, whose influence on TRN is well-documented in literature [5].

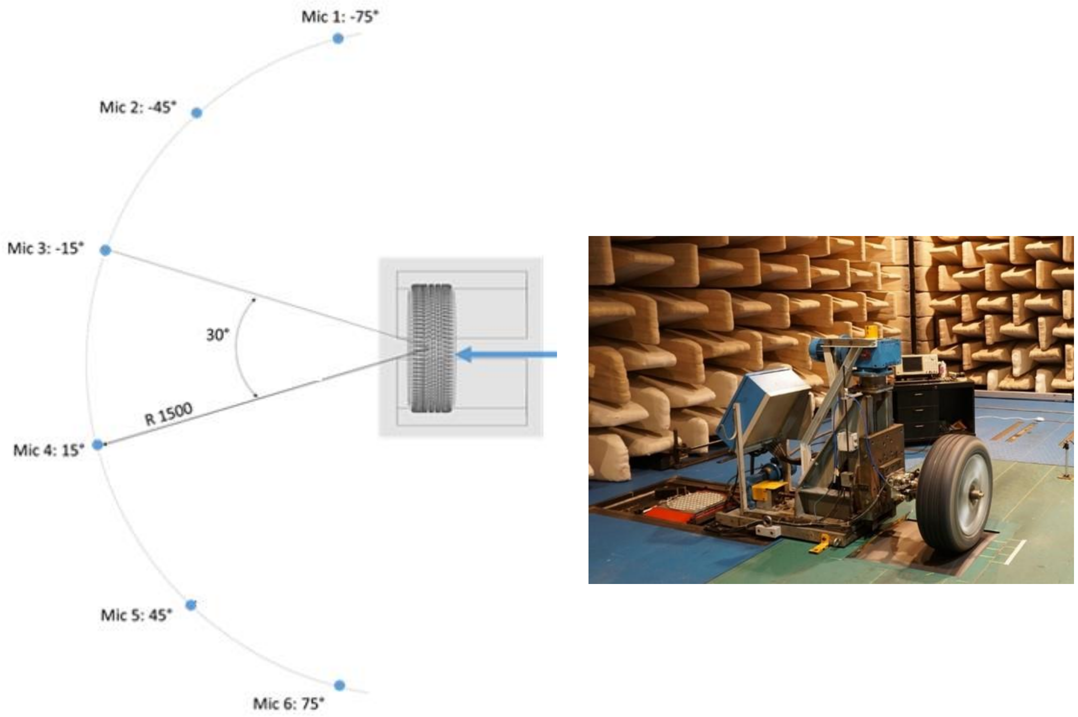
3.1 Tyre/noise measurement

Regarding tyre noise measurements, outdoor and indoor techniques can be adopted. The first ones have the main drawback of being influenced by environmental factors, such as temperature, wind and background noise. These uncontrollable parameters have an impact on the repeatability of tests, affecting the investigation of tyre design parameters on the resulting noise [12]. In order to isolate the TRN, indoor tests can be performed so as to measure the signals in a controlled environment. For these reasons, in this paper, experimental measurements were performed according to an indoor approach.

Indoor TRN measurements are typically performed in semi-anechoic chambers according to the laboratory drum approach. These facilities can reproduce a free-field condition, and the only reflecting surface is the floor. To test tyres in a rolling condition, a drum is installed inside the chamber which can be equipped with different kind of surfaces (sandpaper, coarse or smooth asphalts, etc.). The tyre is mounted on a turret capable of applying a vertical load, so as to replicate realistic operative conditions. The exerted force is dependent on the vehicle on which the tyre will be mounted and it influences parameters that are important for TRN testing, such as footprint dimensions. Once the tyre has been mounted on the turret, a controlled electric motor drives the drum to obtain a given tyre rolling speed.

In this work, a sandpaper road surface was adopted (a homogeneous profile representative of a road without cobblestones), so as to minimize the influence of road roughness on the measured TRN and limiting the attention on tyre parameters. Moreover, tests were performed at three constant speeds, 50 km/h, 80 km/h and 110 km/h. TRN measurements were performed by means of six microphones placed on a semi-circumference with radius 1.5 m with an angular step of 30°, so as to record signals at the inlet, side and outlet regions of the footprint. Figure 2a shows a drawing of the microphones' position and Figure 2b provides a picture of the experimental setup, showing a tyre rolling on drum at constant speed during TRN measurements.

During the experimental campaign, microphones signals were collected as well as tyre operating parameters, in particular tyre revolutions per minute (RPM), inflation pressure and vertical load.



(a) (b)

Figure 2 Tyre/road noise indoor testing according to the laboratory drum approach: (a) far-field microphones positions with respect to tyre footprint centre; (b) a TRN measurement in semi-anechoic chamber.

3.2 Noise-related tyre/road parameters

Once tyre/road noise measurements are performed, the second step is the identification and measurement of noise-related tyre/road parameters (cf. Figure 1). Keeping into account that tests were performed in a controlled environment with the same conditions for all tyres in the dataset, environmental conditions can also be regarded as a property of the collected dataset, and no input parameter is included to model their effect on TRN.

As represented in top left corner of Figure 1, four parameters' typologies are considered to obtain a complete description of the tyre during TRN tests. The first typology is the one of tyre operating parameters. Since they are specific to the performed measurements, the operating parameters are already evaluated during TRN tests. In this work, tyre RPMs and inflation pressure are collected. Tyre RPMs are fundamental since they are strictly related to the frequency of tyre revolutions. Since part of the TRN is periodic with tyre revolutions, its energy is spread all over the considered frequency range according to tyre RPMs [13]. At low speeds, tread pattern noise will mainly have lower frequencies with respect to higher speeds, for which the same harmonics (orders) will shift to higher frequencies. Moreover, increasing tyre speed, a logarithmic increase of the overall sound intensity level is observed [4]. Inflation pressure is important since it influences the contact area, the tyre structural stiffness and the contact forces exchanged between tyre and road [14, 15].

The second typology is the one of tyre footprint parameters. They were evaluated with dedicated measurements, performed with the same vertical load of TRN tests. It is worth pointing out that, in this work, the vertical load is not considered as a noise-related parameter because other footprint characteristics that are highly correlated with the vertical load are already included. As represented in Figure 3, these footprint characteristics are the width, the length and the footprint roundness factor, whose value is the ratio between the footprint area and the area of an ideal rectangular footprint (in case of a rectangular footprint, the roundness factor equals 1 and reaches its upper limit). These parameters were selected because footprint dimensions are related to amplification mechanisms, such as pipe resonances and horn effects, as well as generation mechanisms that take place in the area of contact between the tyre and the road [4]. Footprint parameters are determined by processing the footprint shape, whose measurement can be evaluated through carbon paper or innovative scanners capable of acquiring digital images of the footprint. In this work, the latter approach was applied.

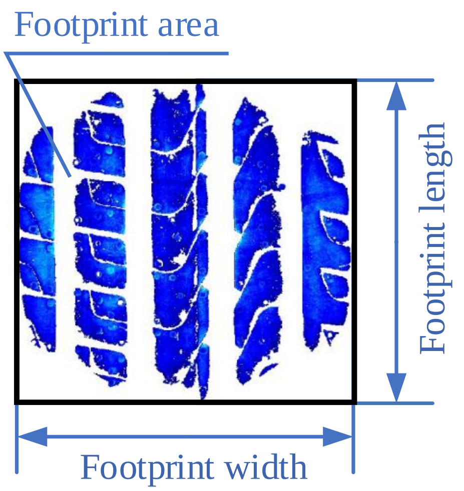


Figure 3 Example of a footprint acquisition and measurement of footprint parameters.

Tyre structure characteristics represent the third typology of noise-related parameters. In this work, three parameters were collected: tyre width, external tyre radius, and rubber hardness. The first two are geometrical parameters, whose values can be simply measured or estimated considering the tyre size nomenclature. These parameters, in addition to their being representative of the general dimensions of the tyre, are strictly related to the curvature of the horn geometry which is established near the footprint area and the TRN amplification due to the horn effect. Rubber hardness is instead related to the material properties and the forces and vibrations that tread blocks undergo when they enter the footprint region of a rolling tyre. Dedicated measurements were required for rubber hardness evaluation. To this aim, Shore A tests [16] were carried out in multiple positions along the tyre circumference and average rubber hardness was evaluated to avoid local effects due to the tread pattern geometry.

Tread pattern characteristics are the fourth typology of noise-related parameters. Among tyre characteristics, the tread pattern is probably one of the most significant for TRN, but reducing it to a limited set of parameters is highly complicated. The tread pattern is related to both amplification mechanisms (such as pipe resonances and Helmholtz resonances) and generation mechanisms (such as tread impact and air pumping). The extraction of meaningful features of very complex tread pattern geometries is not a trivial task to accomplish, and it is difficult to assess which of tread pattern characteristics are the most important ones [5]. For this reason, in this work, a complete 3D scan of the tyres' tread has been measured by means of a laser profilometer.

A high-resolution 3D tyre profile was then obtained, as represented in Figure 4. This data is useful for the extraction of the noise-related tyre parameters discussed in Section 4.2.

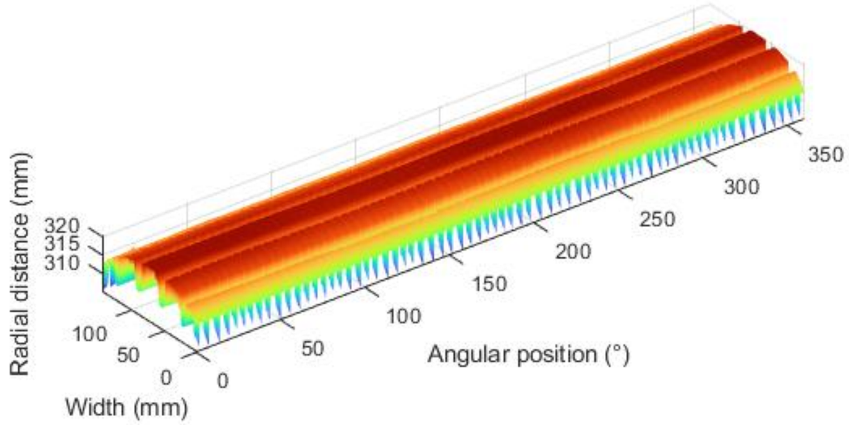


Figure 4 A 3D tyre profile measured by laser profilometer.

4 Data processing

The processing of TRN measurements and of noise-related tyre/road parameters is a fundamental stage for the development of a statistical model. In the following, the processing of output and input parameters is discussed.

4.1 Output parameters

At first, under the assumption of far-field condition, the six microphones' signals were processed to obtain narrowband A-weighted sound intensities. Recalling that the target of the model is the prediction of the complete tyre/road noise during indoor tests on laboratory drum, no separation in tread pattern and non-tread pattern contribution is performed. The average sound intensity is then computed and processed to obtain a 1/3 octave band spectrum, as represented in Figure 5.

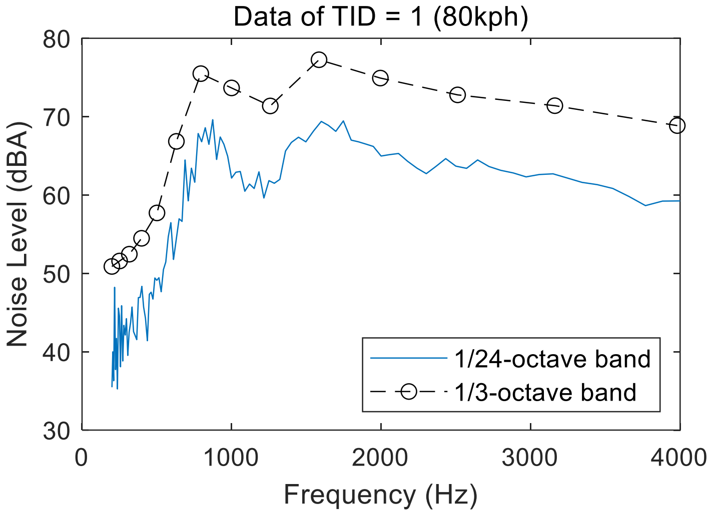


Figure 5 Average sound intensity level in 1/24-octave bands and 1/3-octave bands

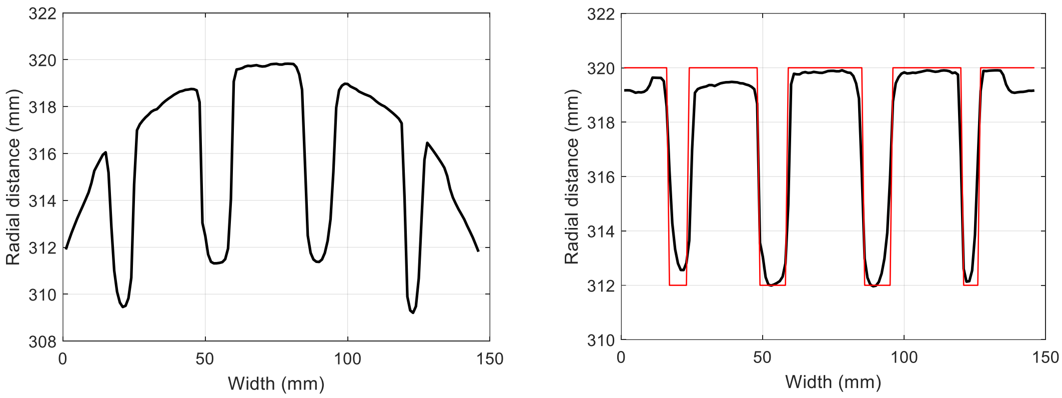
The frequency range of interest has been limited from 200 to 4000 Hz. This choice is justified by the typical trend of tyre noise spectra, whose maximum amplitudes are typically in the 800-2500 Hz range due to pipe resonances and horn effect amplifications and due to the harmonics of the tread impact generation mechanism [4]. 14 bands are present in this frequency range of interest. Therefore, 14 target output parameters are extracted from each TRN measurement. However, it is worth pointing out that, considering that microphones were placed at a distance $R = 1.5\ m$ from the tyre, the far field assumption ($R > 1.6\ \lambda_{max}$) is not verified for the first three bands. Nonetheless, the signals of these bands were still considered as meaningful target outputs and were kept in the dataset.

4.2 Input parameters

In Section 3.2, the collection of four different type of noise-related tyre parameters was described. Some of these parameters can be directly considered as inputs of the statistical model, whereas others require specific processing. In particular, noise-related features should be extracted from the tread pattern 3D scan. Other statistical models, such as Convolutional Neural Networks, may not require this processing stage since they can consider the whole 3D scan as an input parameter.

In this work, the tread pattern scan was processed through a physical approach in order to estimate the harmonics of the tread impact generation mechanism and the related amplitudes.

At first, a tread pattern scan was processed to remove measurement noise and parts of the scan that were not related to the footprint region, such as tyre sidewalls. This step was performed by combining the tread scan with the footprint width (Figure 6a). Then, the tread pattern profile was flattened to reproduce the tyre deformation that the footprint region undergoes at the tyre/road interface. To this aim, the algorithm evaluates the mean value of the radial distance of the treads' surface from the tyre axis and imposes this value as the mean amplitude along the circumferential direction for each lateral coordinate of the tread scan (Figure 6b). Moreover, at this stage, the presence of long grooves is evaluated by analysing the slope of the profile along the lateral direction and its variation along the circumferential direction.



(a) (b)

Figure 6 In (a), a section of the tread pattern scan is shown. In (b), the curvature of the profile has been removed and long grooves have been identified.

From this preliminary processing, two tread pattern parameters were obtained. The first one is the overall width of the long grooves (this value is null for patterns without long grooves). The other input is, instead, associated with the average transversal area through which air can flow, thus including the area of long grooves, lateral grooves and sipes. These two input parameters provide a general description of the amount of air that can flow through the footprint grooves. In this work, the air volume variation at the footprint region was not evaluated in frequency domain since previous studies [7] have revealed that this phenomenon is highly correlated with tread spectrum. The tread spectrum is regarded as sufficient for the description of TRN, so as to avoid having correlated parameters in the set of inputs.

In order to compute the tread pattern spectrum, the pre-processed scan (Figure 7a) is converted along the circumferential direction from the spatial domain to the time domain, taking into account the tyre rotating speed (Figure 7b). This processing is therefore applied to each tyre and each rotating speed considered during TRN measurements. Once time domain signals are obtained, the Fast Fourier Transform is applied and signals are converted in the frequency domain for each lateral coordinate of the scan, thus obtaining a description of the tread pattern in terms tread harmonics amplitudes and relative phases. Eventually, coherent averages over the lateral direction are calculated so as to obtain a single spectrum for the tread pattern. The narrow-band spectrum was then processed to obtain 1/3 octave bands in the 200-4000 Hz frequency range, ending up with 14 tread pattern input parameters (Figure 7c).

Figure 8 shows a synthetic representation of the data processing stage. Starting from TRN measurements and the acquisition of noise-related tyre/road parameters, inputs and target outputs were evaluated for developing the statistical model. In particular, a set of 24 inputs was extracted per each tyre at each rolling speed, for a dataset of 249 samples (83 tyres tested at 3 different rolling speeds). Among the inputs, the tread pattern parameters were computed by processing the tread scans to estimate the tread impact harmonics and other geometrical features related to the air volume inside the tyre grooves. These input and target outputs were then used for the training of the statistical model, which in this work was realized by means of an Artificial Neural Network. Details on this stage of development of the statistical model are provided in the following section.

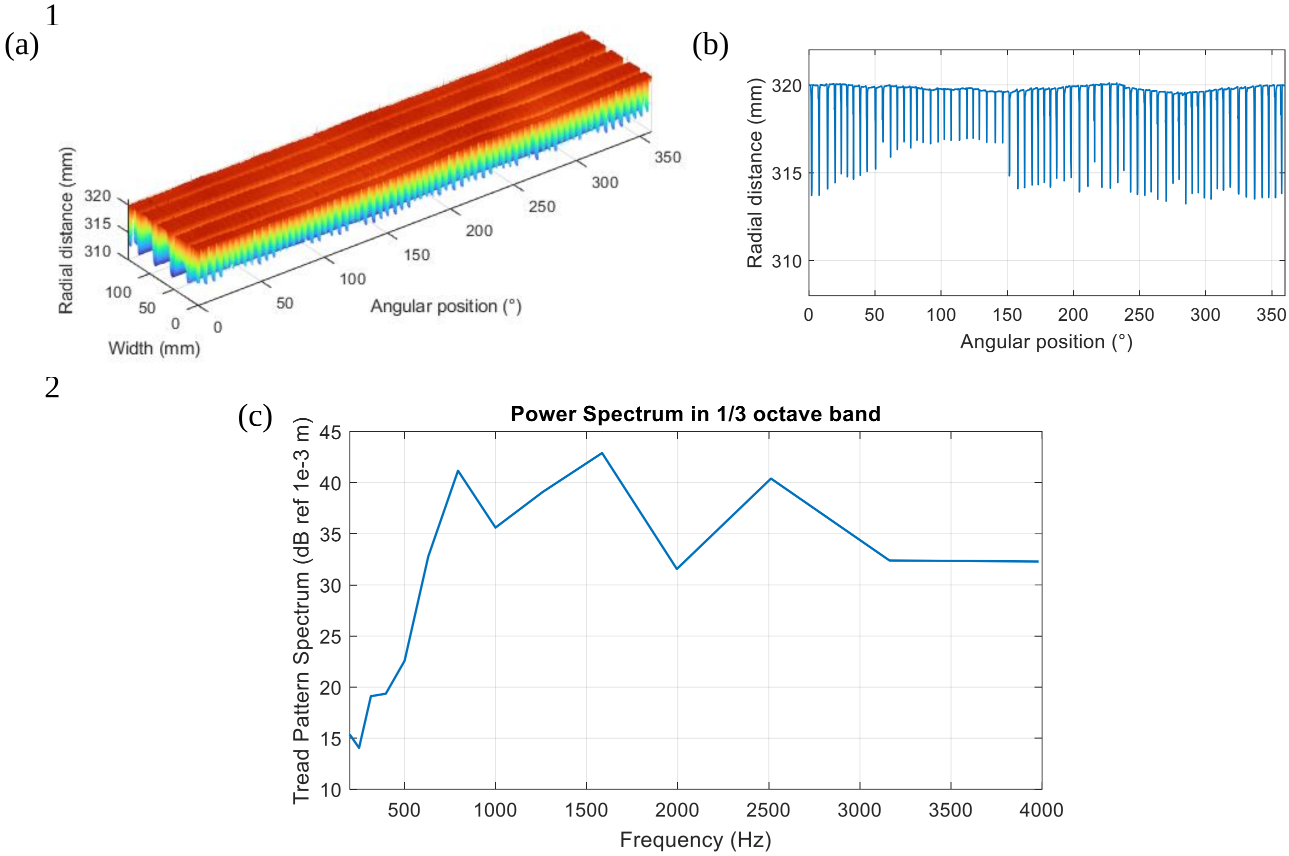


Figure 7 Processing of the tread pattern scan. In (a), a flattened and cropped scan is shown. In (b), the signal is evaluated considering the tread geometry at a specific lateral coordinate. In (c), the average power spectrum of the tread pattern is evaluated in 1/3 octave bands.

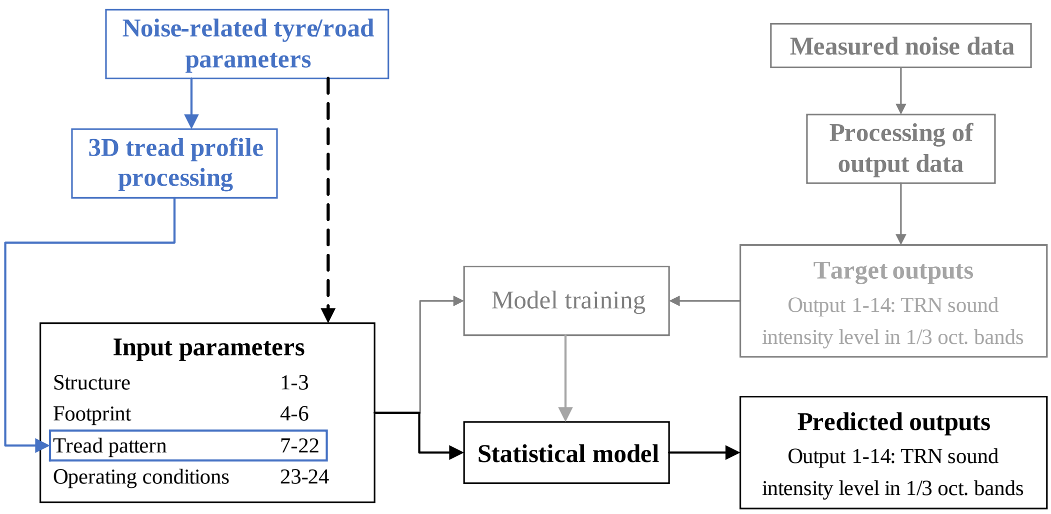


Figure 8 Schematic representation of the data processing.

5 Statistical model

In this work, a simple Artificial Neural Network (ANN) is used to develop a TRN statistical model. This approach is suited to perform regressions of complex non-linear input-output relationships, as the TRN phenomenon considered in this paper, Indeed, neural networks have the possibility to learn complex relationships due to the presence of neurons' layers with non-linear activation functions. Several neural networks architectures can be defined. In this work, a feedforward neural network is used in order to limit the number of tyres to include in the database. Other architectures can be considered, such as convolutional neural networks, however they require larger databases. The considered ANN is made of 24 input neurons, 14 sigmoid hidden neurons and 14 linear output neurons. A single hidden layer is included to avoid complex ANN structures that would lead to a higher number of neurons' weights and biases to be determined during the training process. Indeed, a low number of ANN parameters was preferred to reduce over-fitting issues, provided that the dataset complexity was correctly caught by the model. Instead, the number of neurons in the hidden layer was driven by a parametric analysis that showed that 10-15 neurons are optimal to obtain low errors in the training and test set predictions. A lower number of hidden neurons lead to under-fitting issues (higher errors in both training and test set), whereas a higher number of hidden neurons was related to overfit issues (higher errors in the test set). Eventually, it can be stated that the number of hidden neurons is related to the dataset complexity and a parametric analysis should be performed if the ANN targets are TRN measurements different from the ones considered in this paper.

During the training process, a Levenberg-Marquardt backpropagation was used. Overfitting is one of the problems that can occur during the training of the neural network. This happens when the network becomes so accurate in the prediction of data in the training set that it is not able to generalize the result. Two solutions were adopted to avoid this: early stopping and regularization. The first technique consisted in monitoring the validation error and in stopping the training when the validation error increased for a certain number of iterations. In this work, the early stopping was reached after 5 iterations that did not meet the validation error requirement. The second method adopted to improve the generalization of the network was the introduction of a regularization performance parameter γ to modify the cost function of the training process and reduce the amplitudes of the neurons' weights and biases. In this work, a γ = 0.9 was used and the network was forced to have a smoother, less likely to overfit response. This regularization solution was defined based on a parametric analysis targeted to the reduction of the test set error induced by overfit of the train set, resulting in optimal values of 0.9-0.95 for the considered ANN architecture with 10-15 hidden neurons.

Usually, an ANN is trained by processing inputs divided into three different data groups called training, validation and test sets [17]. In this work, the samples of the dataset were randomly split so that the 70% was in the training set, 15% in the validation one and the remaining 15% in the test set. Once the parameters were selected, the network was trained and the results were evaluated. At first, the root mean square error (RMSE) between the target outputs and the predicted ones was evaluated, as reported in Table 1. It can be observed that the performances of the test set, whose data were not included in the training process, were similar to those of the training and validation sets, showing no overfitting problems. In Figure 9, the trend of the error with frequency is represented for the test set only, thus highlighting that errors are mainly related to the lower frequency bands. In Figure 10, a comparison between the prediction and the measurement of the target outputs of some samples in the test set (focusing on 80 km/h speed only) is represented in terms of 1/3 octave band sound intensity spectra. Promising results were obtained, still considering that a larger dataset could be used to further improve the ANN performances.

Table 1 Root mean square errors of the train, validation and test datasets.

	Train	**Validation**	**Test**
Root mean square error	2.1 dBA	2.4 dBA	2.3 dBA

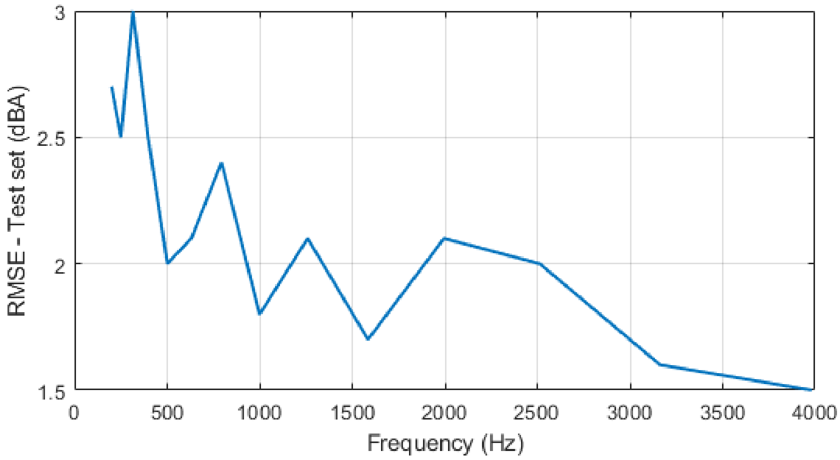


Figure 9 – Trends of the root mean square error for the test set. One-third octave bands in the 200-4000 Hz frequency range were considered.

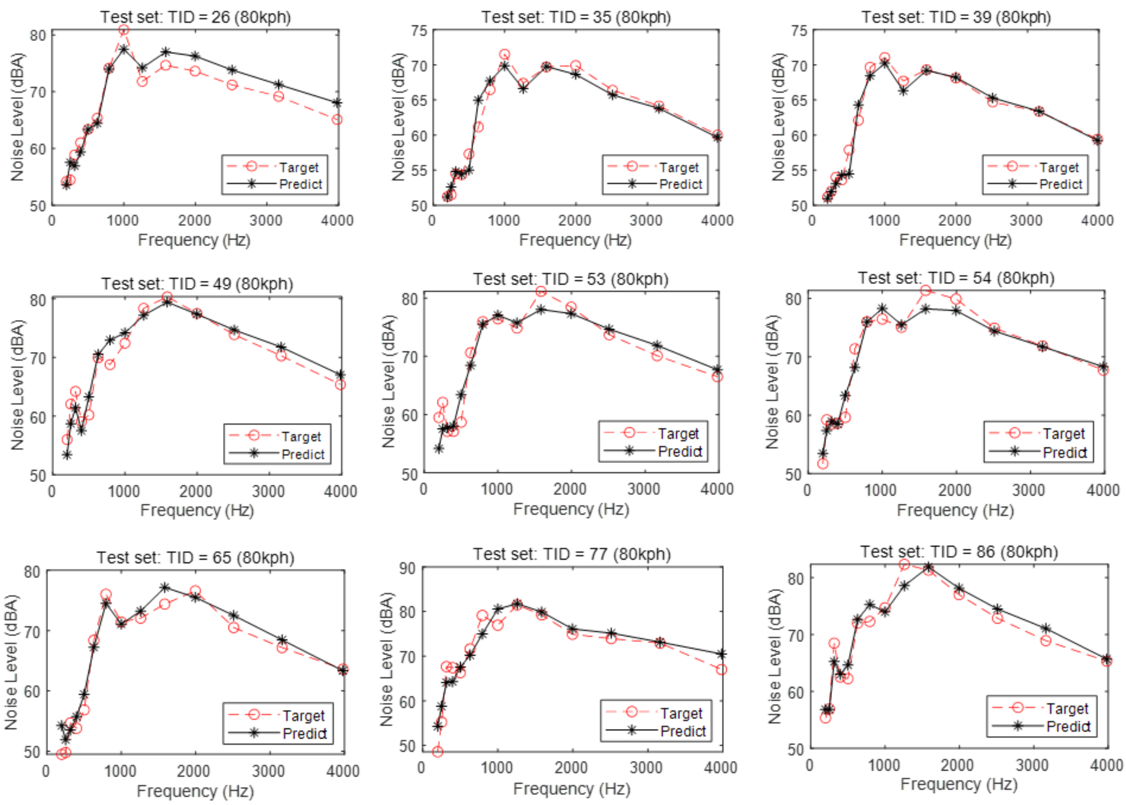


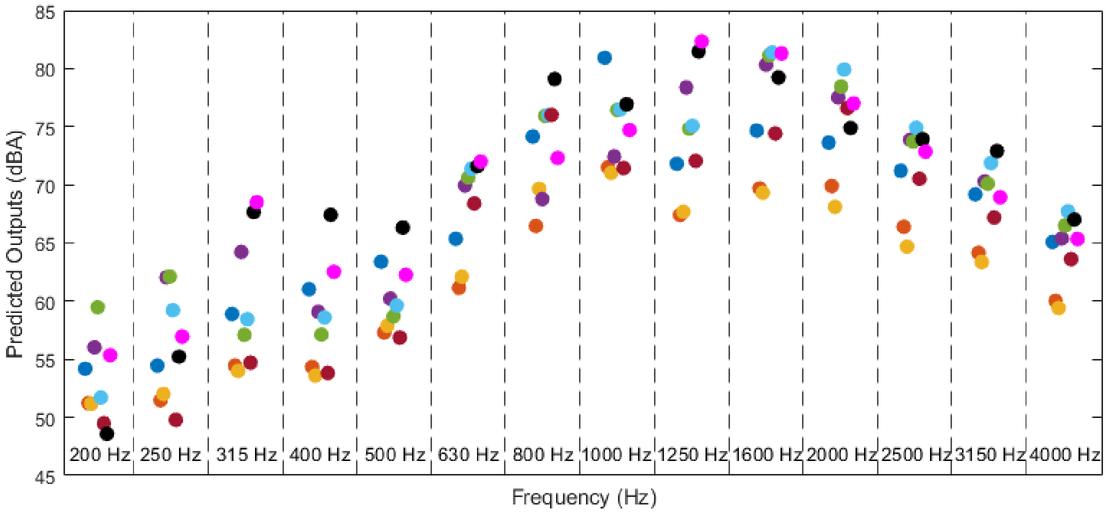
Figure 10 Sound intensity levels in one-third octave band obtained from the ANN estimation (Predict, continuous line) vs experimental measurement (Target, dashed line) of some tyres belonging to the test set.

6 Discussion

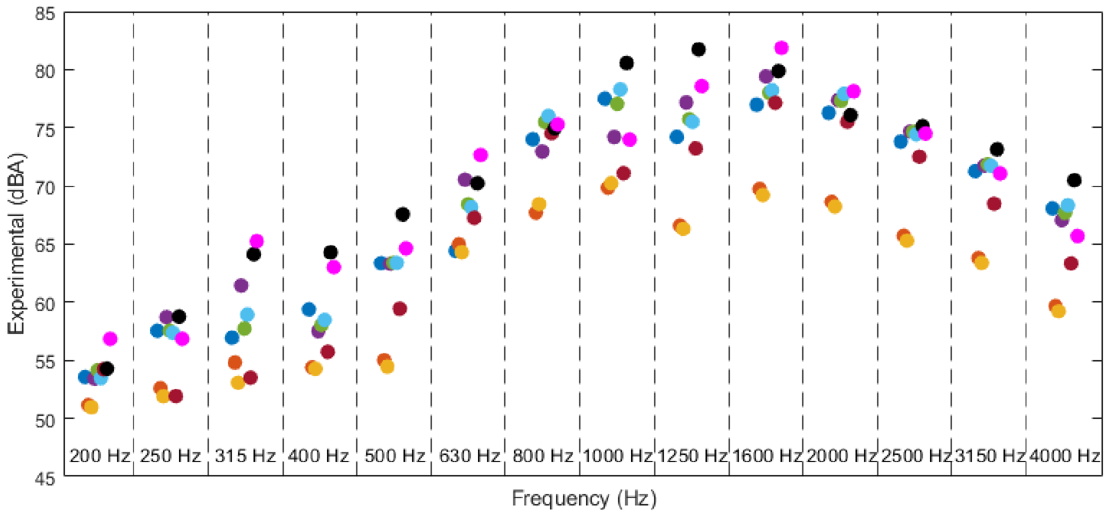
To discuss the prediction capability of the proposed methodology, a comparison only based on the test set was performed, since this data was not involved in the ANN's training process.

In general, considering the quantitative prediction of the TRN for each sample in the test set, the ANN estimated the target outputs with a RMSE of 2.3 dBA, thus obtaining a level of accuracy that can be regarded as acceptable considering the underlying simple statistical model and the number of available samples. Comparing the predictions with the respective target outputs in terms of sound intensity spectra (Figure 10), the trends with the frequency were correctly reproduced and a quantitative match between the two curves was also obtained for the whole frequency range, except for some specific bands of certain tyres. From these results, designers could estimate which frequency range mostly contributes to noise emission and investigate changes induced in TRN by variations of specific tyre parameters, so as to optimize the acoustic indexes.

Another possible usage of the statistical model is the evaluation of TRN rankings among a given set of tyres. In this work, the TRN measurements and the ANN estimations represented in Figure 10 were considered to investigate the possibility of performing a predictive ranking. A unique colour was given to each tyre and the results were represented as a coloured dot per each frequency band (Figure 11). This representation allows to assess which tyre has the lowest sound intensity for each band. Moreover, absolute values can still be read in order give higher priority to frequency ranges with higher sound intensities and assess how many decibels of difference are present between the spectra of tyres. This type of representation can be generated starting from the ANN predictions (Figure 11a) or experimental measurements (Figure 11b). Comparing the two figures, a general agreement among the two results can be observed, even if some frequency bands show inversions of the rankings. Considering that the assessment of rankings is of much interest to the automotive industry, improvements will be sought in the project follow-up through the inclusion of more samples in the database, also enabling the possibility of considering more input parameters and more complex statistical models, such as CNNs.



(a)



(b)

Figure 11 Each tyre represented in Figure 10 is given a specific colour. The ranking among tyres is represented per each one-third octave band using the predicted outputs (a) and the experimental measurements (b). The ranking capabilities can be discussed comparing the two representations.

7 Conclusions

In this paper, a methodology to develop a statistical tyre-road noise (TRN) model has been described and applied for the prediction of sound intensity levels during indoor tests. The main focus of the work was the identification and processing of noise-related tyre parameters. A total of 24 input parameters were extracted for each test condition, for a database covering 249 samples (83 tyres tested at 3 different rolling speeds). Since indoor tests were performed in a controlled environment, no environmental-related input parameter was included in the database. It is worth recalling that the developed database is specific to the considered test conditions; therefore, if TRN measurements are executed differently (e.g., a different drum surface or microphones' positions), a new database must be developed according to the new conditions. As for the outputs, 14 one-third octave bands A-weighted sound intensity levels were considered for each test condition. Once the training of the statistical model was completed, results were discussed both in terms of prediction of TRN absolute values and ranking capabilities. The obtained results are a first step towards the prediction of tyre noise and show the potential of the presented methodology in terms of selection of descriptive parameters and features' extraction procedure. Despite the simple structure of the ANN used in this frame, promising results have been obtained, thus opening the way to further research activities to improve prediction accuracy.

It is worth mentioning that the results of a statistical model are also dependent on the dimension of the database used to train the model. Indeed, more samples in the database can be beneficial to generalize the relationships between inputs and outputs and confirm the promising results obtained so far. In this work, tyres belonging to different typologies (Summer, Winter, Ice, All Season and Mono-pitch) were considered, however, due to the high complexity of tyres' design, their number may still be too limited for a proper generalization of the model and better results could be obtained considering larger datasets. Further improvements to obtain more robust predictions will be the target of follow-up activities, supported by an extension of the database and the evaluation of more complex statistical models (such as convolutional neural networks) or the inclusion of additional input parameters.

As the final aim is developing a tool for tyre designers to predict the acoustic performances of virtual prototypes, the follow-up of this activity will necessarily include the assessment of prediction capabilities starting from fully virtual inputs only. To this aim, it is of interest developing tools capable of extracting the very same input parameters starting from virtual models of tyre prototypes. This way, the statistical model could replace both TRN measurements and the experimental measurements required for evaluating the noise-related tyre input parameters, thus avoiding the costly and time-consuming production of physical prototypes. Moreover, the possibility of performing acoustic predictions through statistical models is of interest even if very detailed tyre virtual models are available. Indeed, the state-of-art deterministic modelling approach to obtain the very same outputs of the ANN presented in this work relies on treaded FE tyre models. To simulate the sound radiation due to tread impact, at first the tyre dynamics has to be solved in time-domain, taking into account very demanding meshing and time step requirements to obtain reliable solutions up to 4kHz. Vibro-acoustic simulations are then employed to post-process the structural response and evaluate the sound radiation due tyre vibrations. According to the authors experience, in general these simulations require 2-3 days on a 64 cores high performance computational node. Timings can differ depending on the specific tread pattern geometry to be simulated and other model parameters. Moreover, non-negligible human time is still required to setup simulations. On the other hand, the presented ANN training process requires few minutes and noise predictions can be evaluated in few seconds on a common laptop. Nonetheless, deterministic and statistical modelling approaches have different advantages and can still be considered as complementary tools to support an acoustic-oriented tyre design.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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