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Original article

An artificial neural network approach to modelling absorbent asphalts acoustic properties

Giuseppe Ciaburro [a], Gino Iannace [a,*], Mohamed Ali [b], Abdullah Alabdulkarem [b], Abdullah Nuhait [b]

[a] Dipartimento di Architettura e Disegno Industriale, Università Degli Studi Della Campania Luigi Vanvitelli, 81031 Aversa, Italy
[b] King Saud University, College of Engineering, Mechanical Engineering Department, P. O. Box 800, Riyadh 11421, Saudi Arabia

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ABSTRACT

Sound-absorbing asphalts are particularly useful for reducing noise emissions from vehicular traffic. This solution is perfectly suited for urban areas, in fact the use of sound-absorbing asphalt represents a noise control measure with a negligible environmental impact. In the present work, the results of an experimental investigation on sound-absorbing asphalts were reported. First, the characteristics of the sound-absorbing asphalts used were experimentally found. Then, the measurements of the sound absorption coefficient of the asphalt specimens were investigated. In the final part, numerical simulation model with artificial neural networks of the acoustic coefficient were compared with the data obtained from the measurements. The neural network model showed good Pearson correlation coefficient values (0.894) which can be used with good accuracy to predict the sound absorption coefficient.

1. Introduction

Transport infrastructures are the main sources of noise pollution in Europe, and if we exclude people who live near airports and railway lines, traffic flow is the main source of human exposure to noise pollution. In recent years, there has been a constant and significant increase in noise levels in the environment, mainly due to the high number of vehicles in circulation, the kilometers traveled, and the increase in vehicle speed. In urban centers, road traffic is the main source of noise pollution, to which administrations place a limit by adopting traffic plans, which provides for a series of coordinated interventions to improve road traffic conditions in these areas (Khan et al., 2018; Heinecke-Schmitt et al., 2018; Pouikli 2019; Montes-González et al., 2018). Noise levels resulting from road traffic above a certain threshold are associated with negative health effects. The World Health Organization (WHO) recommends to decrease the noise levels emitted by daytime road traffic to be under 53 dBA Lden level. While, for exposure to night noise, the WHO recommends to decrease the noise levels emitted by road traffic during the night hours to be under 45 dBA Lnight, since above this level the noise is associated with negative impact on sleep. Furthermore, WHO recommends the use of technologies that reduce the propagation of noise from the source to the population exposed to the noise pollution of the road traffic (World Health Organization, 2018). Vehicle noise can be attributed to two main causes: noise produced by the engine, and noise due to the motion of the vehicle. The noise produced by the engine depends on the speed and acceleration of the vehicle and derives mainly from the following elements: engine, intake and exhaust system, transmission shafts, cooling fan, gearbox, and hydraulic pumps. The noise due to the motion of a vehicle depends on the speed of the vehicle and the type of pavement and generated mainly from rolling, vibrations, tire-road interaction, aerodynamic drag (Sheng, 2012). In cars, the noise caused by the motion of the vehicle is prevalent over that produced by the engine except for the acceleration phases. The rolling noise depends on the speed of the vehicle and on the characteristics and conditions of the road surface: type of aggregates, roughness, and grain size, degree of degradation, acoustics properties. Instead, they have less influence on the weight of the vehicle, its acceleration and the characteristics of the tire: load, tread design, tire pressure, and degree of wear. Rolling noise is due to three main causes: collision of the tire on the surface, air that is compressed in the spaces in the tread caused by deformation generating vibrations,

* Corresponding author.
E-mail addresses: giuseppe.ciaburro@unicampania.it (G. Ciaburro), gino.iannace@unicampania.it (G. Iannace), mali@ksu.edu.sa (M. Ali), aalabdulkarem@ksu.edu.sa, anuhait@ksu.edu.sa (A. Alabdulkarem).

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adhesion phenomena between surface aggregates and tires. (Thompson and Dixon, 2004; Lu and Jen, 2010). The rolling noise produced by the tire is at low frequency with values below 1000 Hz, this at the low speeds typical of urban roads. In the case of wet asphalt, the noise increases by about 5–10 dBA. Aerodynamic noise grows with the collision of the vehicle against the air and depends on the speed of the vehicle, but also on the profile of the bodywork. This noise has components in the frequency ranging from 500 Hz to 3000 Hz with a level that changes from 45 to 60 dBA. For speeds greater than 60 km/h, the impact of rolling noise caused by the tires grows and becomes predominant for speeds above 80 km/h. For speeds greater than 100 km/h, the impact of aerodynamic noise becomes predominant (Iwnicki et al., 2019). The issue of traffic noise has been underestimated and got little attention, so much so that most of the built-up areas have been developed right in the vicinity of important road arteries, and it is therefore difficult to imagine the implementation of a remediation work so extensive acoustics, unless huge investments are made. The problems of noise disturbance connected to road infrastructures provided for possible interventions that can be classified into two categories: the first includes all the solutions applicable in the design phase that tend to reduce noise at the source. The second consists of all possible mitigation interventions following paving roads (Ouis, 2001; Griffiths and Langdon, 1968; Bluhm et al., 2004; Stansfeld et al., 1993). To treat this issue, we can use sound-absorbing asphalt which reduces noise and helps in rainwater drainage. This type of asphalt is produced from aggregate granules bonded with bituminous conglomerate. The asphalt obtained has an alveolar structure characterized by high percentage voids that keep the resistance of the material almost unchanged. The draining layer, thanks to its reduced macro-texture with negative roughness, acts as a sound absorbing septum as the sound waves penetrating inside the pores are reflected infinite times transforming into thermal energy (Tiwari et al., 2004; Yamaguchi, et al., 1999). For these materials, absorption is characterized by the asphalt thickness and the inert materials diameter. Draining asphalts have a void percentage of more than 15% greater than conventional asphalts. In addition, the noise produced by the rolling of the tires on the asphalt has lower frequency components that are less annoying for the human ear. The tire that impacts the road pavement at high speed compresses the air that surrounds it, trapping it between the rubber groove and the bottom, thus generating rolling noise. This bearing, under the wheel, expands after the passage and generates resonance in the air, the primary cause of the noise. The asphalt with a high percentage of voids allows the air to pass under the contact area without compressing too much and therefore limiting the effect of the resonance. The mechanical properties of a compacted bituminous conglomerate strongly depend on the percentage of internal residual voids. The percentage of voids essentially depends on the particle size composition of the aggregates, which is characterized in the compaction phase (Arenas and Crocker, 2010; Peeters et al., 2010). Recently, several authors have attempted to create mathematical and numerical models with the aim of simulating the asphalt acoustic properties. Attenborough (Attenborough and Howorth, 1990) studied the effects of porous road pavement on the transmission of noise from an acoustic perspective. This study confirmed that rough pavement surfaces cause a significant increase in ambient noise levels. Hamet (Hamet and Berengier, 1993) studied the relations between sound absorption and pore structure. This study developed an extensive phenomenological model often used to describe the porous asphalt. The parameters necessary for the mathematical expressions contained in the model can be determined by measurements. Meiarashi (Meiarashi et al., 1996) developed a silent flooring considering a porous elastic surface. In this study, it was shown that the noise reductions of this pavement are higher than those of an asphalt drainage pavement for both cars and trucks, respectively of 13 and 6 dBA. Gołebiewski (Gołebiewski et al. 2003) investigated the noise generated by some vehicles on the dense asphalt and porous asphalt. They then used subjective drive-by noise assessments to evaluate the performance of the two floors. The study highlighted that exposure to sound and the pavement surface coefficient can be used as acoustic features of a pavement surface. Mun (Mun, 2010) based on measurements of the acoustic absorption coefficients of porous asphalt concrete pavements, they have shown that a better attenuation of the noise is obtained by set the air vacuum percentage, the asphalt gradation and the thickness of the road surface. Chu (Chu et al., 2017) studied several mixtures of a porous asphalt pavement. The authors showed that reducing the porosity percentage from 25% to 12% caused negligible changes in the reduction of pavement noise, changing the frequency characteristics of the acoustic absorption. The analytical, correlation and simulation models developed for the acoustic properties forecasting underestimate or overestimate the experimental results, therefore they do not allow satisfactory predictions to be obtained. Until now, the only method to obtain reliable or very reliable results is the experimental method, but it is very expensive both in terms of time and costs. Artificial Neural Network-based algorithms can represent a valid tool for solving modeling problems of the acoustic properties of materials. The search for an appropriate model structure allows us to simulate the connection between the material features and the sound absorption coefficient via computer, to make prediction of the acoustic characteristics of the material, according to the parameters used (Iannace et al., 2020). In the present work, sound-absorbing asphalts are experimentally tested and the characteristics of the asphalts are found. After that, the measured acoustic properties of the material are reported and analyzed. A numerical model was developed and validated with the experimental data.

2. Materials and methods

2.1. Absorbent asphalts characterization

Traditional conglomerates are made up of three layers of grain size and thickness decreasing upwards. The base layer has the function of withstanding the stresses without reporting permanent deformations and of resisting any settling of the underlying soil. The connection or binder layer joins the base with the wear layer, transmitting the vertical action of the loads without undergoing permanent deformation. Finally, the wear layer, the surface part of the flooring, is made up of aggregates with resistance to sanding and whose characteristics must be studied to obtain the required performance. It is precisely in the creation of the wear layer, responsible for the safety and ride comfort, that the search for different mixtures has been concentrated in response to the various traffic and climatic needs, arriving at the formulation of high-performance bituminous conglomerates (Moore et al., 2001; Liu and Cao, 2009). Draining asphalt is a material characterized by high porosity, it is created by mixing aggregates of different diameters, leaving small voids that are called pores. The result is therefore an open and porous flooring: in case of rain these characteristics allow the water to go down to the waterproof layer and, thanks to a slight slope, to make it slide towards the edges of the road. This asphalt has significant advantages in terms of longer life, about 30% more than normal asphalt, and in terms of absorption of vehicular noise (Putman and Kline, 2012; Field et al., 1982). A good sound absorption is guaranteed by an asphalt with a at least 20% percentage of voids. In addition, the aggregates must hold a high rate of medium diameter aggregate and a low rate of fine diameter aggregate. To acoustically characterize this type of asphalt, many specimens that has compound mixture were examined. The mixture is composed of aggregates bonded together with a binder, to present a percentage of voids. The study was conducted on specimens assembled with 5.3% bitumen and a void percentage equal to 17%. Table 1 shows some parameters of the asphalt specimens used for the measurements.

Four types of specimens were assembled by changing the size of the aggregate pieces. The dry and wet weight was measured for each specimen. Fig. 1 shows a specimen with the dimensions. The specimens have been sized to be compatible with the instrument for measuring the acoustic coefficient.

Fig. 1. Specimen used in the experiment with the dimensions.

2.2. Acoustic properties measurements

To begin, the measurements of the acoustic properties of the asphalt were carried out: the measurements of the acoustic absorption coefficient at normal incidence were carried out as indicated by the procedure contained in the ISO 10534–2 standard (ISO (1053)4–2, 1998) As mentioned earlier, the asphalt specimens were assembled into four types by changing the dimension of the aggregate in the mixture. The method describes the procedure for measuring the acoustic parameters of small specimens. The measurements were carried out with the help of an impedance tube, with the following specifications: 10 cm of internal diameter and 56 cm of length. Two ¼ " microphones are positioned inside the tube. The impedance tube with these specifications returns the acoustic absorption coefficient of the specimen for frequencies ranging from 200 Hz to 2000 Hz. A pink noise is introduced inside the tube through a loudspeaker located at one end of the tube. The specimen is housed on the opposite side of the tube, resting on a rigid circular wall of 10 cm in diameter. The transfer functions returned by the two microphones inside the tube are combined to form the absorption coefficient. Fig. 2 shows the impedance tube (Kundt tube), it is possible to identify the support in which the specimen is housed (on the left), and the section in which the microphones and the speaker are housed (on the right).

The measurements were made for each of the four specimens to limit the effects of irregularities in the specimens. For each measurement, the specimen was removed from the tube and subsequently re-housed in it. The result represents the average value of the absorption coefficients obtained in the four acquisitions.

2.3. Exploring artificial neural network algorithm

The term machine learning refers to a series of algorithms that allow the automatic knowledge extraction from large databases. In this way operations such as classification, identification, segmentation are performed independently by computer systems without the aid of human beings. These operations are performed by the machines thanks to the ability to learn of artificial intelligence, which gives computers the ability to make decisions without the need to perform preordained tasks. The increasingly complex industrial processes can be managed independently by the machines simply by relying on the data collected during the training phase (Alpaydin, 2020; Mohri et al. 2018). More specifically, an algorithm based on machine learning can extract common characteristics and models from a dataset provided in the training process and apply them to new datasets never seen before. The data are used to form models and to learn extracted knowledge. These algorithms are trained using different techniques decided by the type of activity that we must make (Carrasquilla and Melko, 2017). In supervised learning, the training data sets contain labels indicating whether each item is appropriate or not, for example, if the expected output value is detected or the class planned is returned. In this case, the algorithms are trained to fit the models in order to learn to detect right occurrences in the new data (Bottou et al., 2018). Machine learning-based models have recently been developed to address different problems (Hardt et al., 2016; Iannace et al., 2018; Ward et al., 2016; Iannace et al., 2019b; Pathan et al., 2019). In analogy to the functioning of the human brain, artificial neural networks (ANNs) are a very important field within artificial intelligence. The purpose of this class of algorithms is to develop numerical models capable of supporting human beings in decision-making processes using innovative techniques. Neural networks are based on elementary components that perform actions like the common functions of a biological neuron. These elements are organized similarly to how they occur in the brain. In addition to looking like the brain they have several brain features. An essential feature of the ANNs is the ability to learn, generalizing from previous experiences to new behaviors, managing to extract key features from a data set. A neural network transforms a set of independent variables $\times = (x_1, \ldots, x_n)$, defined as network inputs, into a set of dependent variables $y = (y_1, \ldots, y_k)$, which represents the network output using a nonlinear mathematical function. The output returned as result depends on a set of values $w = (w_1, \ldots, w_n)$, called weights. In a network, the correlation between output and input can be exemplified through the following equation:

$$y = f\left(\sum_j w_j * x_j + b\right) \tag{1}$$

Here:

- x_j is the jth input
- w_j is the jth weight
- b is the bias
- y is the output

Table 1
Parameters of the asphalt specimens.

Specimen	Height [m]	Diameter [m]	Weight [Kg]	Wet weight [Kg]
A	0.061	0.099	0.990	1.010
B	0.056	0.099	0.950	0.965
C	0.059	0.099	0.970	0.989
D	0.065	0.099	1.000	1.022

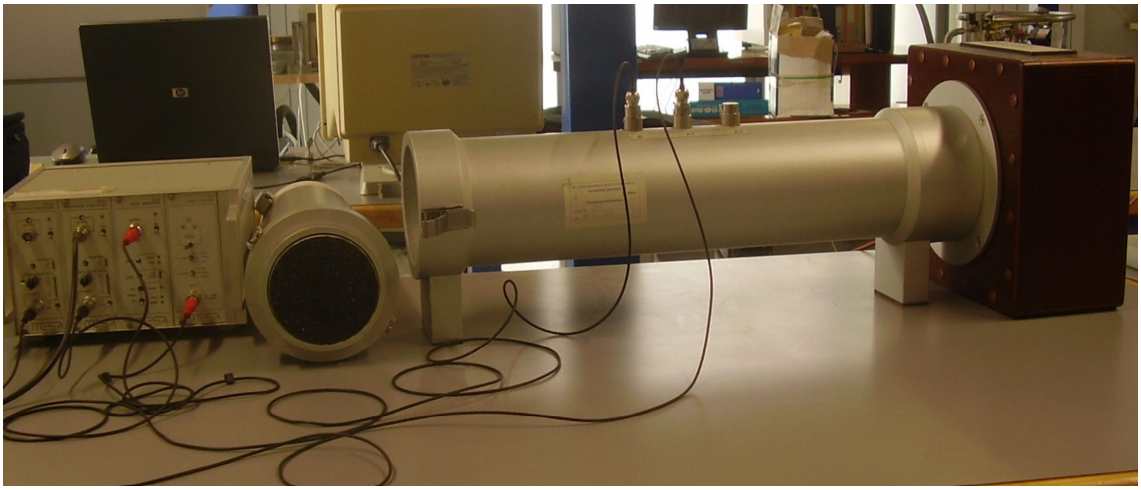

Fig. 2. Impedance tube device used in this work for measurement of the acoustics properties of the sound-absorbing asphalt.

- f is the activation function

Weights and biases express the knowledge that artificial neurons learn during the training phase and that they will use later to make predictions. The function f is called the activation function: it is a threshold function that is activated only if the signal output from the neuron exceeds the threshold, in this way the signal is transferred to the next successive layers. Nonlinear functions as sigmoid or logistic functions are examples of activation functions (Iannace et al., 2019a). As anticipated, the weights are adjusted during the training phase through an iterative procedure. This procedure requires intense computational effort and uses a certain number of input-target pairs, called training sets. In training, we search for the values of weights that minimize a specific error function (Rojas, 2013). The architecture of a neural network has three typical elements, each of which has artificial neurons: input, output, and hidden layers. The signals supplied to the system as inputs reach the output layer, passing through the neurons present in the internal layers, as shown in the following Fig. 3.

External signals are passed to the network through the input nodes, connected to each node of the hidden layer. Each node processes the received signals by applying the transfer function and transmits the result to subsequent nodes.

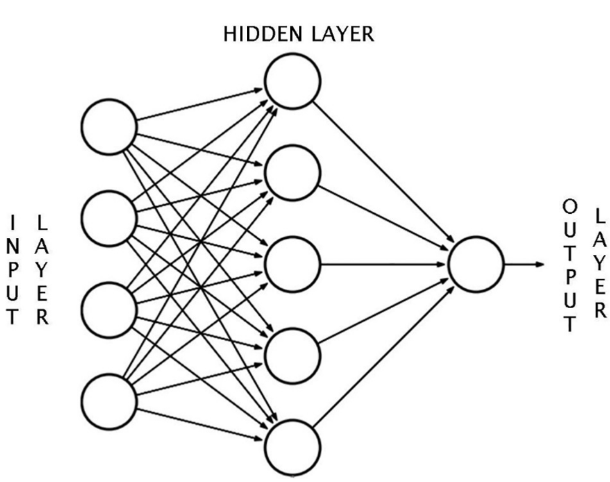

Fig. 3. Artificial Neural Network architecture with nodes and connections.

3. Results and discussion

3.1. Measurements results

To perform the measurements of the sound absorption coefficient, the asphalt specimen were assembled, in four type (A, B, C, D). Specimens were assembled with a draining mixture with a granulometric variety of these components: small and large basalt, sand, and filler. To subdivide the different types of aggregates, sun sieves are used with standardized sizes and shapes. The asphalt specimens were housed into the impedance tube to evaluate the sound absorption coefficient. In Fig. 4 are reported the results of these measurements for asphalt specimens of four distinct types. The normal incidence sound absorption coefficient, in the frequency range 200 Hz – 2000 Hz, was measured. The measurements were performed for the four types of specimens in the following three configurations:

- **Specimen with dry material**: For this configuration, the sound absorption coefficient of the asphalt was measured for a specimen with 10 cm of diameter and 6 cm of thickness.
- **Specimen with wet material**: For this configuration, the sound absorption coefficient was measured on a specimen soaked in water. The acoustic performance of the asphalt in wet weather differs: In these meteorological conditions the voids are partially occupied by water which infiltrates the structure of the pores. To study the behavior of the material in this configuration, the asphalt specimens were submerged in a water for about 20 days, after which the specimen was removed and weighed. Subsequently, the specimen was subjected to the acoustics measurements using the impedance tube (Kundt's tube). Table 1 shows the weight value of the specimen after these operations.
- **Specimen with dirty material**: For this configuration, the sound absorption coefficient of the sound-absorbing asphalt was measured on a soiled specimen. The road is subject to wear and tear over time through a slow deterioration process. Specific maintenance operations can guarantee the sound absorption characteristics unchanged over time. In the laboratory, a partially deteriorated sound-absorbing asphalt specimen was simulated: to do this, a layer of earth was added to the upper part of the specimen to simulate the actual conditions that arise due to the flow of traffic and the surrounding environment. A layer composed of sand, potting soil, weeds was added to the specimen.

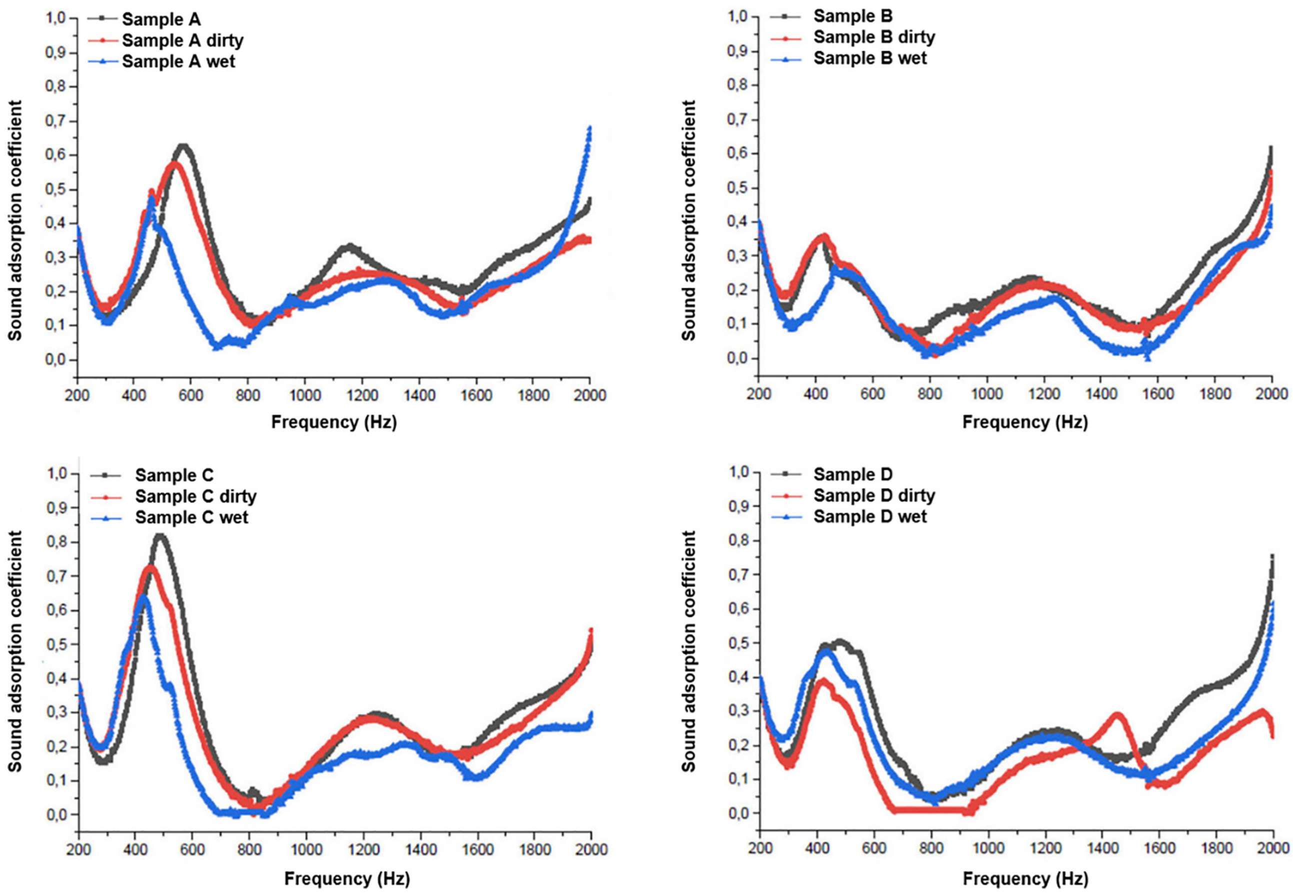

Fig. 4. Sound absorption coefficient values of A, B, C, D specimens and for three configurations: Specimen with dry material, Specimen with wet material, and Specimen with dirty material.

Fig. 4 shows the trends of the acoustics measurements versus the frequency for the four specimens (A, B, C, D) in the three configurations just described.

Fig. 4 allows us to analyze the differences shown by the four specimens in the three configurations provided. Starting from the first specimen denoted as specimen A we can see that the measurements reaches a maximum value of about 0.6 in correspondence with a frequency equal to 600 Hz: This happens for specimen A in a dry configuration: We can notice a bell pattern for the low frequencies ranging from 400 Hz to 800 Hz. The same trend is also confirmed for the configurations from dirt and wet only that there is a decrease in the maximum value which drops to 0.55 for dirt and to 0.5 for the wet. In addition, the bell curves move towards the lower frequencies. In the medium frequencies ranging from 800 to 1600 Hz we notice a curve trend with a central maximum but more flattened with a maximum value ranging from 0.3 to 0.2. In the high frequencies starting from 1600 Hz there is an increasing trend in the sound absorption coefficient, this trend is confirmed for all three configurations. Overall, we can see that the dry specimen is the most performing one, then we have the dirty one and finally the wet one. The lower performance is due to the clogging of the pores by dirt and water which reduces the acoustic performance of the asphalt. A similar argument can be made for specimen B in which, however, we observe a drastic reduction in performance, particularly at low frequencies. In this area, the bell-shaped curves characteristic of the measurement for many porous materials has a maximum which drops below 0.4. For medium and high frequencies, the trend of specimen B are comparable with those of specimen A. Also, for specimen B, the differences between the performances of the three configurations are confirmed: the dry specimen is the best performing then we have the dirty one and finally the wet one. In this case, the dirty specimen recorded values comparable with the dry specimen. Specimen C is the most performing one: we can see that the measurements reaches a maximum value of about 0.85 in correspondence with a frequency equal to 500 Hz: This happens for specimen C in a dry configuration. Specimen C is the lighter one, as shown in Table 1 to demonstrate a greater number of pores. Also, in this case we can see a bell-shaped trend for low frequencies ranging from 300 Hz to 700 Hz with a lowering of the frequencies compared to the previous specimens. For medium and high frequencies, the trend of specimen C are comparable with those of specimen A and B. The differences between the performance of the three configurations are also confirmed for specimen C: the dry specimen is the most performing then we have the dirty and finally the wet one. In this case, the dirty specimen recorded values comparable with the dry specimen. Specimen D confirms the trends already seen for the other three specimens with poorer performance. The difference with the other cases is shown by the dirty configuration which, unlike the other cases, proves to be the least performing. Perhaps due to a greater presence of contaminants that limit its performance, for frequencies ranging from 650 Hz to 900 Hz.

3.2. Simulation model based on ANN

The quality of the forecasts made by a numerical model depends on the characteristics of the data. A good data preparation process, in fact, represents a crucial phase for the construction of a predictive model and focuses on organizing and preparing the data to obtain the maximum benefit from the analysis of such data. Typically, data preparation includes the following: Data Cleaning, Feature Transformation, and Feature Selection. Data cleaning is about cleaning information, removing noise or other inconsistencies that could cause problems in the data analysis process. It also explores and prepares the data for the next steps. In a good data preparation process, it is necessary to identify what are the relevant characteristics that impact on the analysis and construction of the predictive model. Identifying these characteristics allows you to know what influences your data most and consequently also the future decision-making process. The goal in this phase is to identify the smallest set of characteristics that best describe the problem that you want to study. In some cases, the need to change the format or the comparison between the quantities analyzed is required to avoid obtaining misleading results. In our case we have variables described by distinct units of measurement which determine clearly different ranges of data variability. This can represent a problem in the model training phase as it can impose a different importance among the variables that cannot be traced back to a real physical phenomenon. To remove the effect deriving from the units of measurement, we can perform the standardization of the variables. This procedure allows the comparability of variables with different distributions. Standardized variables are non-dimensional values, that is independent of the unit of measurement, which measure the deviation of the distribution values. It is obtained by calculating the difference between each value and the arithmetic mean in relation to the standard deviation, as indicated by the following formula:

$$x_s = \frac{x - mean(x)}{sd(x)}$$

The variable scaled which takes on the following properties:

- mean = 0
- standard deviation = 1

In this work we want to develop a neural networks-based model capable of predicting the values of the sound absorption coefficient, based on some characteristics of a sound-absorbing asphalt. To measure algorithm performance, model validation must be performed. Validation tends to verify the predictive ability of the model using previously unused input data. The validation of the model is intended to avoid excessive adaptation of the model, problem that arises in the case of excessive adaptation to the observed data due to an excess of parameters compared to the observations. The model validation procedure involves dividing the data set into two subsets: training set and test set. The first set will be used to train the model, while the test set will be used to test the prediction capabilities of the model. In this study, the input data was divided as follows: a training set equal to 70% of the data obtaining 8517 observations, and a test set equal to the remaining 30% of the data obtaining 3651 observations. The division was done randomly.

The simulation model was developed using an algorithm based on an feed-forward artificial multilevel neural network with 5 input variables (frequency, dry specimen, dirty specimen, wet specimen, weight), with 10 neurons in the hidden layer which returns the acoustic-acoustic property of the sound-absorbing asphalt. The information regarding the type of configuration of the specimen among the three available (Specimen with dry material, Specimen with wet material, and Specimen with dirty material) was inserted in the dataset as a dummy variable. A dummy variable is a variable that assumes a value of 0 or 1, depending on whether a given condition is met or not. It is inserted with the aim of capturing the effect of a qualitative variable on the average value of the dependent variable. This adds three columns containing a binary value (0.1) to the dataset. This column will contain 1 if the type of specimen coincides with that represented by the column, otherwise it will contain 0. To calculate the prediction error in the training phase, the measurements of the acoustic properties are compared with those simulated by the numerical model. An iterative procedure is adopted to adapt the connections weights, minimizing an error function. The weight adjustment procedure includes the following steps: To begin, the derivatives of the error function versus weights are evaluated. The results are then applied to determine the new weights. In this study, the scaled conjugated gradient Backpropagation (SCG) algorithm was used which uses the gradient descent technique to locate the minimum of the error function versus the weights (Daniel, 2013). The architecture of the neural networks-based model is shown in Fig. 5:

Fig. 5 shows the composition of each layer of the neural network. The input layer consist of five data inputs as follows: frequency, dry specimen, dirty specimen, wet specimen, and weight.

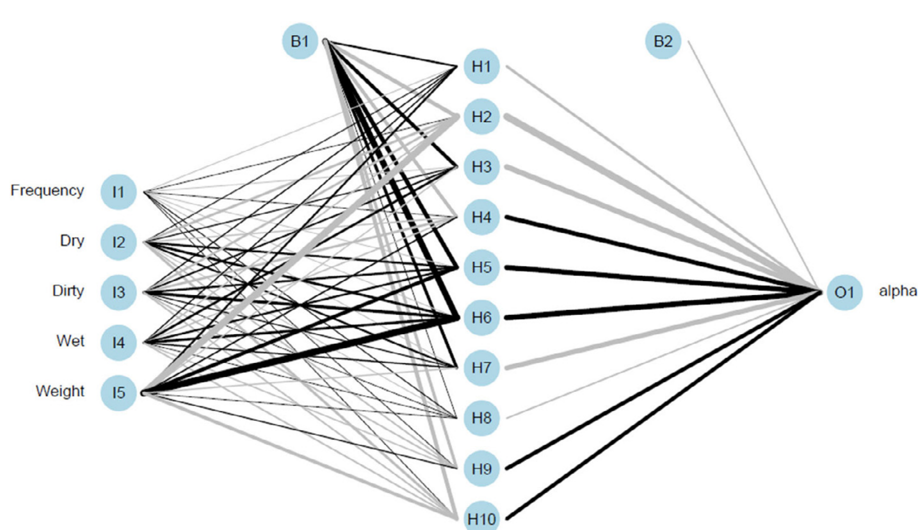

Fig. 5. Architecture of the neural networks-based model.

Table 2
Input layer to Hidden layer weights and biases.

	H1	H2	H3	H4	H5	H6	H7	H8	H9	*H*10
I1	−0,028	0,014	−0,002	0,002	−0,031	−0,008	−0,002	0,086	0,002	0,015
I2	0,074	−1,205	0,428	−0,466	1,006	1,387	0,830	0,000	−0,654	−1,280
I3	0,320	−0,969	0,747	−1,154	1,036	1,883	0,422	0,001	−0,574	−0,641
I4	0,448	−0,372	1,194	−0,462	0,947	1,424	0,687	0,000	−0,467	−0,675
I5	0,885	−5,210	−0,110	0,599	2,498	5,370	−0,400	0,001	0,275	−2,019
B1	0,842	−2,547	2,369	−2,082	2,989	4,694	1,939	0,001	−1,695	−2,596

Table 3
Hidden layer to Output layer weights and biases.

H1 - O1	H2 - O1	H3 - O1	H4 - O1	H5 - O1	H6 - O1	H7 - O1	H8 - O1	H9 - O1	*H*10 - O1	B2 - O1
−1,356	−5,316	−3,915	3,213	3,722	4,108	−3,432	−0,608	2,733	2,614	−0,610

Table 4
Metrics for the simulation model evaluation.

RMSE	MAE	Person's Correlation Coefficient
0.066	0.044	0.894

Ten neurons are contained in the hidden layer. Then, an output layer with the sound adsorption coefficient is obtained. Fig. 5 contains details to understand the features of the processed neural network. The thickness of the connections between neurons of different levels represents the weight that the neuron assumes in the formation of the outcome. Furthermore, the lines colors symbolize the connection sign: black indicates a positive contribution; gray indicates a negative contribution (Møller, 1993; Ripley et al., 2016). Tables 2-3 reports the weights and biases returned by the numerical model.

Table 4 shows the RMSE, MAE and the Person's correlation coefficient for the simulation model.

From the analysis of Tables 4 we can see that the numerical model has a low error and a good correlation between simulated data and measured data. Now, we assess the sound absorption coefficient versus frequency for the simulated and measured values with the neural network model for the sound-absorbing asphalt. In this way it will be easier to estimate the achievement of the simulation model.

From the analysis in Fig. 6 we can see that simulated acoustic properties rest on the measured ones. In some cases, they fit better,

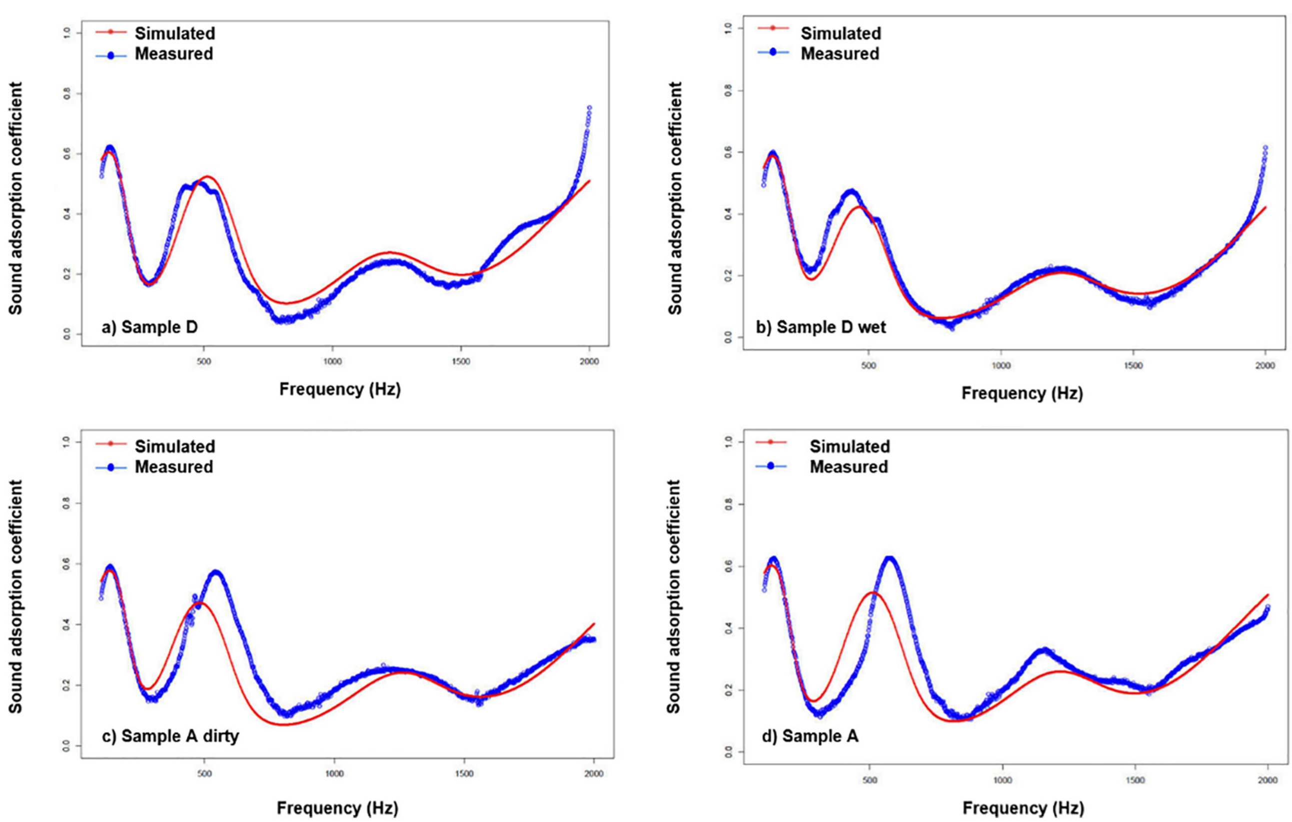

Fig. 6. Comparison of acoustics properties - simulated versus measured. The curves of the measured data are shown in blue, the simulated data curves in red. The acoustic absorption coefficients of 4 specimens randomly selected from those available were simulated. The data used for the simulation was not used for network training. a) Sample D; b) Sample D wet; c) Sample A dirty; d) Sample A.

for example in correspondence of anomalies due to the uncertainties of the measures.

4. Conclusions

Sound-absorbing asphalts are particularly useful for reducing noise emissions from vehicular traffic. In urban areas they often represent the only achievable measure given the negligible environmental impact. In the present work, the results of an experimental investigation on sound-absorbing asphalts were reported. First, the characteristics of the sound-absorbing asphalts used were examined. Then, the measurements of the sound absorption coefficient were reported and examined. Ultimately, the outcomes returned by the artificial neural networks-based model were compared with the data obtained from the conducted measurements. The neural network model returned good values for Pearson's correlation coefficient (0.894), to represent a good adaptation of the model to the data with the return of forecasts consistent with those labeled. The usefulness of a model for predicting the acoustic properties of the material of a road pavement can concern different aspects. For example, the model can be adopted to simulate the acoustic behavior of the road pavement in correspondence with models for which no acoustic measurements have been made.

Declaration of Competing Interest

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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