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Simulation of Acoustic Properties of Plaster Matrix Composite MATERIAL Reinforced with Corn Stem Fibers

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Abstract: Environmental sustainability and environmental protection are key to shaping the built environment. The use of environmentally sustainable materials in architecture is essential to transform urban centers into modern, sustainable cities, reducing the pollution of air and natural ecosystems, lowering gas emissions, and improving the energy efficiency of structures. In this study, corn processing waste was used as a reinforcing material to create a plaster matrix composite material for use as a sound absorption material. Specimens of two thicknesses were created, and the sound absorption coefficient (SAC) was measured by applying the normal incidence technique. Subsequently, a simulation model for predicting SAC using Artificial Neural Network (ANN) algorithms was utilized to compare the absorption performance of the specimens. The fibers extracted from the corn stem significantly improved the sound absorption performance of the gypsum matrix specimens. This is due to the increase in the porosity of the material caused by the adhesion between the fiber and the plaster which creates air pockets due to the roughness of the fiber. The simulation model appears to be effective in predicting the absorption properties of the material, as indicated by the results.

Keywords: sound absorption coefficient; artificial neural network; corn stem fibers

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1. Introduction

The environmental situation on our planet has become critical, atmospheric emissions are now unsustainable, and global warming has been relentless for more than a century. For this reason, countries' environmental policies have included programs aimed at reducing CO_2 emissions into the atmosphere and a drastic reduction in resources from nonrenewable sources [1]. In this context, construction plays a key role, which is why a change in mentality is needed. In the past decades, environmental problems have become globalized, and the social and economic forces behind them have undergone profound globalization. Indeed, human beings have faced precarious environmental conditions throughout their history. However, environmental-type instances have become more evident and common due to the processes of industrialization and urbanization [2].

Environmental issues, especially those related to climate change induced by human activities, continue to have an important place within the global political agenda. The environment makes available resources that are necessary for human life in addition to the natural resources that are used by industrial-type activities. From that perspective, the environment acts as a repository, providing the basic sustenance for human societies [3]. The resources that are made available are both renewable and nonrenewable types. Consequently, when there is overuse of the latter it is possible to have a shortage of the former as well, as can happen with fossil fuels. In addition, in the process of consuming resources, humans produce waste products. From this point of view, the environment serves as a repository for waste, either through its absorption or its recycling into other substances that are useful or at least cause less harm. When wastes turn out to exceed the capacity of the environment to absorb them, it results in environmental problems, namely pollution and scarcity of resources [4].

To reduce waste generation, it is necessary to adopt policies to reuse and recycle resources. Reuse and recycling are the cornerstones of the waste hierarchy and represent the deep essence of the circular economy, being able to return environmental and economic benefits [5]. In the transformation processes of raw materials that lead to the creation of finished supply chain products, production residues are obtained that can be destined for disposal as waste or for recovery. In the case of recovery, through appropriate treatments, the waste returns to being considered a resource to be used in defined production processes to make new products [6]. The material, in this case, is given the name of a second raw material, that is, a new raw material derived from waste recovery or recycling. Agro-food residues are an important source of waste if not properly treated. Fibers extracted from the processing of some crops can be recovered and used as raw materials to produce building materials [7]. From the cultivation of corn, for example, a plant fiber is extracted that can be used for a variety of purposes. Yılmaz [8] studied the characteristics of corn stem fibers from a mechanical point of view. The author extracted corn stem fibers by means of water maceration, alkalinization, and enzymatic procedures. Maceration in water restored maximum breaking strength and breaking toughness. The enzymatic treatment, while resulting in a reduction in breaking toughness and elongation in the fibers, returned increased initial moduli and breaking toughness in the alkalized fibers. Sari et al. [9] examined the effects of varying concentrations of NaOH on the chemical, physical, and mechanical properties of corn stem fibers. The study revealed that the treatment removed hemicellulose and lignin from the fibers and reduced moisture content, resulting in significant improvements in the fibers' chemical, physical, and mechanical properties. Youssef et al. [10] have produced, by casting and compression molding, a composite material using corn stem fibers and recycled low-density polyethylene (R-LDPE). The final product was evaluated to determine its mechanical properties by assessing the relationship between fiber loading and moduli, tensile strength, and hardness. The results showed that as fiber loading increased, moduli and tensile strength also increased, but hardness decreased. Ibrahim et al. [11] used corn stem fiber as a reinforcing filler to produce a biodegradable composite on a thermoplastic corn starch matrix. The study showed that the use of stem fiber improved the mechanical and thermal performance of the composite films. A reduction in the density and moisture content of the films was measured, and a lower resistance to biodegradation was also found.

Noise is a key component of environmental pollution, and it can affect the quality of life in urban and suburban environments [12]. Therefore, the attention of researchers has focused over time on finding materials that can contribute to the insulation and soundproofing of domestic environments [13]. Soundproofing interventions aim to minimize the transmission of noise between two environments and reduce the acoustic energy that propagates through the air from a disturbing environment to a receiving environment [14]. Sound-absorbing measures, on the other hand, aim to control the reflection of sound on the walls of a room and thus adapt the propagation of sound within a room to suit one's needs. In the construction of new buildings, as well as in the renovation of existing ones, it becomes crucial to use materials with acoustic properties to ensure acoustic comfort in buildings [15]. The choice of materials with acoustic properties derived from plant waste can make an important contribution to environmental sustainability. Several researchers have measured the acoustic properties of fibers derived from plant waste from corn cultivation. Lyu et al. [16] have produced a composite material from corn stem fibers immersed in a polylactic acid-based matrix. The composite was made through a hot mixing and pressing process, and panels with micro-cracks, air cavities, and linen felt were prepared from the resulting material. The results show optimal acoustic performance at high frequencies. As the panel thickness increases, the peak of the SAC increases, and the frequency shift moves towards lower frequencies. Sari et al. [17] studied the sound-absorbing features of material made from an unsaturated polyester matrix and corn stem fibers. The authors showed that as the fiber content increases, acoustic performance improves at low frequencies. At high frequencies, the sound-absorption performance depends on the disposition of the fibers in the composite. Tang et al. [18] used untreated corn stem simply washed with distilled water and then air-dried. The authors produced specimens by arranging several layers of fibers and measuring acoustic performance: Increasing the layers did not return an improvement in sound absorption, while it shifted the peak toward lower frequencies. Instead, increasing the cavity back to the absorbing panel may increase the absorption coefficient at low frequencies. Kaamin et al. [19] produced sound-absorbing panels by filling egg carton containers with corn stem fibers. The authors measured the SAC with the impedance tube and found good acoustic performance at medium frequencies (1000 Hz). Berliandika et al. [20] studied the sound-absorbing performance of a composite made from corn stem fiber immersed in a latex adhesive-based matrix. The authors treated the fiber by immersing it in a 5 percent sodium hydroxide (NaOH)-based solution for two hours. The results of SAC measurements by an impedance tube showed that the composite with untreated fiber had better sound absorption performance than the treated fiber. In addition, the authors tested the panels by arranging a cavity, finding that, in this case, the SAC shifts toward low frequencies depending on the stiffness of the composite layer by increasing the viscous damping effect.

In this work, the absorption characteristics of a composite produced with the fiber extracted from corn cultivation waste were characterized. First, sound absorption coefficient (SAC) measurement campaigns were prepared as prescribed by UNE-EN ISO 10534-2 [21]. In addition, to expand the study into unexplored domains, the experimental measurement procedure was compared with a simulative analysis. The simulative study was conducted by adopting a data-driven approach. The simulation was performed by exploiting the data collected in the measurement campaigns and obtaining automatic knowledge extraction using Machine Learning-based algorithms. The potential of corn stem fibers extracted from corn crop waste (corn stem fibers) as a reinforcement material to produce a plaster matrix composite was analyzed. To make the panels, corn stem fibers were mixed with the plaster-based binder in a ratio of one to three by weight, respectively. Specimens of two thicknesses, 6 and 12 mm, were prepared. Then, the SAC was measured, and subsequently, the findings of the measurement procedures were compared with the results obtained with a simulation model centered on ANN.

The structure of the article is as follows: Section 2 covers the materials and methods used in this study, including the techniques for preparing samples from corn cultivation waste. Then, the methodologies adopted for the measurement of SAC using the impedance tube technique are presented. Next, the technologies adopted to set up the ANN-based simulation model are illustrated. In Section 3, the results obtained from the ANN-based simulation model are compared and discussed, and in the final section, the overall results of the work are summarized, and potential real-world applications of the developed technology are discussed.

2. Materials and Methods

2.1. Characterization of Corn Cultivation

Corn is a raw material derived from the cultivation of herbaceous plants of the grass family (of the Maydeae type, species Zea mays) which is used in various forms for animal and human sustenance and energy production. Corn is native to Central America, with grain production amounting to around 1,150,000,000 tons (about 195,000,000 hectares) to date, according to official world data supplied by the Food and Agriculture Organization of the United Nations (FAO) [22], and in recent years, corn is the most widely grown grain in the world. Almost a quarter of the world's grain production distribution is located between the U.S., China, Brazil, and Mexico. Corn cultivation can produce significant amounts of agri-food residues throughout the supply chain, which are of interest in other industrial processes and depend on the purpose of cultivation and the type of processing involved [23]. In recent years, there has been an increase in the use of corn cultivation waste for artisanal purposes through its processing into fibers, which can become an important resource in support of environmental sustainability policies. These natural fibers have gained importance in the world market in recent years as their demand has increased in industrialized countries, replacing synthetic ones in various applications [24].

The purpose of this work is to study the acoustic characterization of fiber obtained from the corn stem, through the development of creating sound-absorbing panels for environmentally sustainable architecture. Thus, the focus of the use of this material will be sound absorption, generally in enclosed spaces. The use of natural materials can facilitate the replacement of synthetic materials, which require industrial development. The focus is on the use of corn cane fibers, which are obtained from the stem of the same plant [25]. Given the large production of this crop in Ecuador, no problems are expected for the commercial production of the acoustic panels that can be obtained, since it is grown in large quantities, especially in the Andean areas of the country.

In recent years, natural fibers have been considered raw materials to produce sound-absorbing panels at a reduced cost compared to synthetic materials. These fibers generally have good acoustic, thermal, and insulating properties. In addition, they do not cause adverse health effects and are available in large quantities as a residual product of other industrial processes [26,27].

The best areas for growing and harvesting corn, based on their climate, are the Andean regions, Central America, and Mexico, where great genetic diversity has been observed. Corn is one of the most significant crops within the Andean areas because of the area devoted to its cultivation, making it one of the largest production and food systems for people. In the Ecuadorian highlands, corn cultivation is one of the main drivers of the economy, due to the large amount of area dedicated to its cultivation, which generates production reserved mainly for the food sector. The most widely cultivated corn in the mountainous region of Ecuador is the yellow floury type found in Carchi, Imbabura, and Pichincha. White floury corn is grown in the central Sierra zone, especially in Tungurahua, Chimborazo, and Bolívar, and corn called Zhima or white amorochado is grown in the southern Sierra zone such as Cañar and Azuay. Currently, 29 varieties of corn have been identified in Ecuador, of which 17 are grown in the highlands.

2.2. Preparation of Specimens

Corn cane of the "Chaucho mejorado" type, with the following characteristics, was used for the preparation of the specimens: yellow kernel, floury texture, low height (1.20–1.40 m), resistant to plant inclination and bending, early, good kernel quality. This corn variety is mainly grown in temperate areas such as Imbabura Province (González Suárez Sector) for food production (Figure 1a). However, it is possible to exploit the waste from its cultivation to produce, for example, soundproofing panels using its fiber and bark.

Harvesting takes place in April during the ripening stage. Light green and purple stems were chosen, formed by a hard, compact woody layer with a cylindrical base that was simple, straight, strong, and gnarled (8–38 knots). During the collection of this material, internodes measuring 15 to 20 cm and a general plant height of 1 to 3 m were also evident. The material has a crop cycle of 125 to 210 days from sowing to maturity. Sample analysis was carried out before harvesting the stems which was used to assess and status of the corn plants. This analysis was aimed at determining the degree of maturity to continue with the fiber crushing and drying process. As a result, it was revealed that not all stems were in the same state of maturity, so stems ranging from 2 to 2.5 cm in diameter had to be selected. Once the plants were selected, a quantity of 56 stems was collected over two consecutive days (Figure 1b).

Next, the stem was separated from the root, leaves, flowers, and fruits, which were not needed for this procedure. The treatment explained below was carried out on all selected plants (Figure 2a). With the stems obtained, the crushing step was consecutively carried out, that is, the stems were passed through an electric machine to extract the juice from the cane (Figure 2b).

Figure 1. (**a**) Corn production plot at flowering and ripening stage in the González Suarez sector. Imbabura, Ecuador; (**b**) selected stems from the corn-growing field.

Figure 2. (**a**) Process of separating unnecessary parts of the plant; (**b**) crushing in a machine to extract juice from the stem; (**c**) drying the crushed fiber exposed to the weather for a period of two days (48 h).

In this process, each of the stems was cut and divided into small parts so that they could fit into the machine and all the superfluous juice could be extracted from the plant so that only the bark and fiber were obtained. Then, the crushed fiber was placed outdoors for the drying stage for a period of two days (Figure 2c).

One of the most important aspects to take into consideration when producing a sound-absorbing material consisting of fibers is its durability. In this case, it was possible to show that, through the drying phase at room temperature, the fiber of the corn stalk contracts to easily handled brittle filaments. Generally, this happens when it is allowed to dry from 6 months to 1 year.

To accelerate the drying process, artificial drying was performed in an oven [28]. The fiber was then placed in an oven at a temperature of 60 °C for about 6 h, and then the weight loss in grams experienced by the fiber was evaluated. This was used to compare the drying status between weather-exposed fiber and oven-exposed fiber through a controlled procedure. The fibers used for the test had an initial weight of 95.5 g, while at the end of the drying process, they showed a reduction in weight at 91.2 g. Thus, a difference of 4.3 g from the initial weight was found, returning a percentage reduction of 4.5 percent.

The use of a binder such as plaster helped to increase the durability of the fibrous material and the functionality of the panel. The selection of this type of binder has two key advantages: first, it is an easily accessible material, and second, it allows this composition to be developed manually.

Use of gypsum, due to its low production cost, aesthetic finish, and installation, is one of the most widely used resources for interior finishes, cladding, and walls in buildings. The behavior of this material with the addition of fibers, both natural and artificial, has been studied for several years. Gypsum needs firing earlier than when it is mixed with water, and once mixed, it hardens. Gypsum is a natural stone with the chemical formula $CaSO_4 \times 2H_2O$ (calcium sulfate dihydrate), which treated at temperatures between 120 °C and 1000 °C, loses the water of crystallization, changing its composition and chemical formula, which becomes $CaSO_4 \times 1/2H_2O$ (calcium sulfate hemihydrate). Different types of gypsum are produced by treating the mined material at different temperatures. Gypsum is a material that changes its behavior in contact with water. In the hydration phase, gypsum is mixed with water, and calcium sulfate dihydrate returns. In this phase, gypsum is gradually added to the water until the mixture reaches saturation. The amount of water in the hydration phase conditions the mechanical behavior of the product, which generally reduces its strength with more water. Later, in the curing phase, the material hardens by losing its plasticity and forming a three-dimensional coagulated structure where Diberot crystals are joined by weak Van del Waals forces of molecular cohesion. The hydration process of gypsum yields a porous crystalline product composed of small, randomly oriented needle-shaped crystallites and larger particles. The mechanical properties of the hardened plaster are mainly determined by the closely interconnected crystalline structure and the remaining porosity of the material.

The plaster used in this study is the fine-grained plaster of type C6 finishes according to the EN 13279-1 standard (Table 1).

Table 1. Plaster technical characteristics.

Feature	Value	Feature	Value
Dry density	0.75 g/cm^3	Types of Plaster	C6
Purity index	>80%	Compressive strength (7 d)	4.0 Mpa
Mixing water	65%	Flexotraction strength (7 d)	3.0 Mpa
Working time	10–15 min	Surface hardness	>70 Shore C
Sieve retention 0.2 mm	≤5%	Reaction to Fire	A1

Plaster has limitations in its use due to its permeability and brittleness, so for some time, researchers have been trying to improve its characteristics by producing plaster-based composites with the addition of reinforcement. From the combination of a brittle matrix and an elastic reinforcement, it is possible to obtain a composite with improved mechanical and acoustic characteristics.

Beginning with the dried fibers that were exposed to room temperature, each of the dried stems was cut and crushed to a size of about 5 mm × 5 mm.

Next, all the cut fiber was collected to perform sieving, using a metal sieve, through which the residue was filtered and then assembled with the plaster-based binder. This technique was repeated several times until the required amount was obtained to make all the specimens needed for measurements. For the plaster-based binder to act, a percentage of water was incorporated, relative to the amount of the binder, so that their particles could be compacted and could adhere to the fiber (Table 2 shows the mixing water rate of each of the samples).

Table 2. Mixing water in reinforced composite.

Thickness (mm)	Corn Stem Fibers (gr)	Plaster (gr)	Water (gr)	Mixing Water Rate (%)
6	45	72	90	77
12	65	122	130	70

Next, specimens were assembled in wooden molds with circular holes (35 mm in diameter) to allow SAC measurements in the impedance tube. Specimens with thicknesses of 6 and 12 mm of corn stem fibers composite material were assembled (Figure 3). Table 3 shows the weight percentage of each of the assembled composites.

Figure 3. Samples for measurement in the impedance tube.

Table 3. Weight percentage of components in composite specimens of different thicknesses.

Thickness (mm)	Corn Stem Fibers (%)	Plaster (%)	Water (%)
6	21.7	34.8	43.5
12	20.5	38.5	41.0

2.3. SAC measurement Using Impedance Tube

The present work studies the possibility of making sound-absorbing panels based on corn stem fibers. The methodology involves the use of a binder that allows the fibers to join and mix, such as plaster. The acoustic properties of the composite material were measured through tests based on the ISO 10534-2 standard [21] carried out with an impedance tube. The standard allows for the calculation of SAC from the measurement of the surface impedance of the material under normal incidence by exploiting an impedance tube. The measurements should be conducted by taking a normalized approach so that the performance of different materials can be compared. The instrumentation used in this study is an ACUPRO Spectronics impedance tube that allows for the measurement of SAC in a specific range frequency (50 Hz–5700 Hz). The tube dimensions consist of a 34.9 mm inner diameter, a 41.3 mm outer diameter, and a 1200 mm length (Figure 4c).

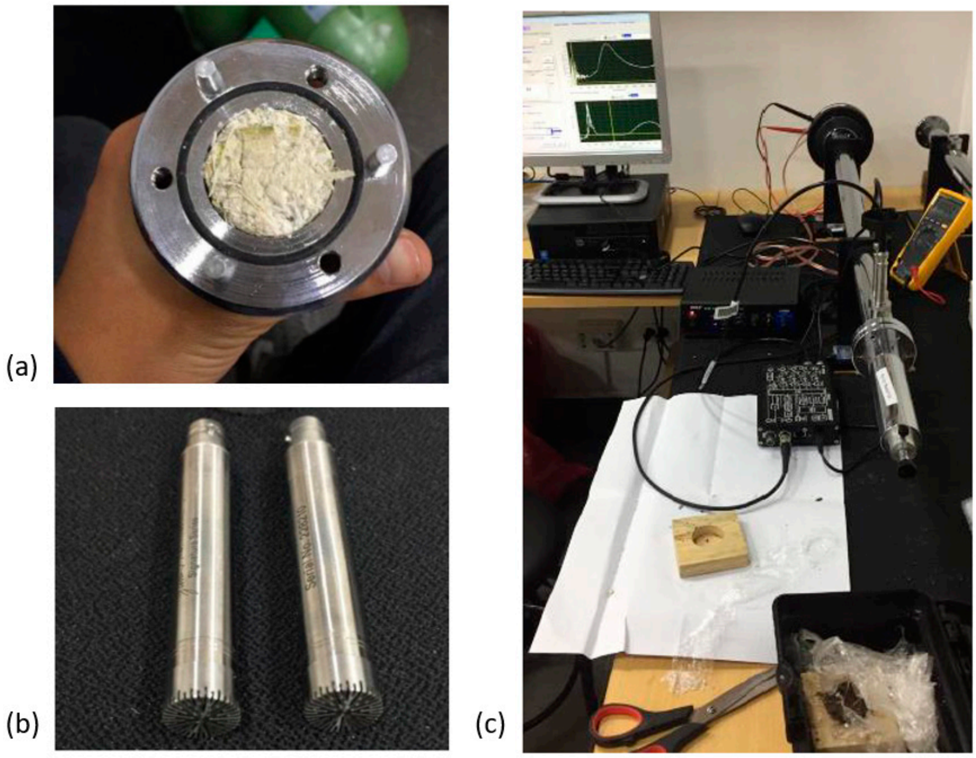

Figure 4. (**a**) Specimen placed inside the impedance tube; (**b**) microphones; (**c**) impedance tube used in this study.

The acquisition system is equipped with a JBL 2426J speaker that emits a 150-dB white signal that is captured by two microphones (Figure 4b) and sent to the ACUPRO software. The software makes 150 surface impedance measurements and calculates the SAC from the average of the measurements. SACs were calculated in a 250 Hz to 5000 Hz frequency range using 1/3-octave bands. The specimens were placed inside the impedance tube (Figure 4a), and to normalize any irregularities in the material, five measurements of the same specimen were made, performing a pro-vine relocation for each measurement.

2.4. SAC modelling Using ANN

Machine Learning (ML) is a field of computer science that studies systems and algorithms capable of learning directly from data without having been programmed in advance [29–31]. Data scientists use ML algorithms to identify patterns within their data that provide them with interesting insights to support strategic decisions of various kinds. ML bases its operation on two different methodologies depending on whether labeled examples are used (supervised learning [32]) or data are provided without any label (unsupervised learning [33]). In this case, having the SAC measures properly labeled, the approach we will take is supervised learning.

Let us now turn our attention to the format of the output in order to distinguish classification algorithms from regression algorithms. Classification algorithms are used when the desired output is a discrete label, that is, it can take one among a set of predetermined values. Regression algorithms, on the other hand, are used to predict continuous outputs. This means that the answer to the originally posed question is represented by a quantity that does not fall within a set of possibilities but can be determined with greater flexibility.

ANNs are adaptive systems, capable of changing their structure in terms of nodes and interconnections based on both internal and external inputs. Artificial neural networks attempt to simulate the functioning of biological neural networks and their component parts [34]. Neural networks are based on the simulation of appropriately connected artificial neurons, which receive stimuli as input and process them accordingly. The simplest case involves individual inputs being multiplied by an appropriate value, called a "weight", and the outcome is then summed. When this sum exceeds a specific threshold, the output of the neuron is activated. Note that the distribution of weight values varies according to the input significance: a valuable input assumes high weight, unlike a less valuable one that assumes a lower value [35].

The multilayer perceptron (MLP) is an artificial neural network model composed of multiple perceptrons [36]. It consists of an input layer, which receives the signal; an output layer, which makes a prediction or decides regarding the input; and an arbitrary number of hidden layers, the real computational engine of the network (Figure 5). Each neuron in one layer is connected to all neurons in the previous layer. For that reason, such a network is also called Fully Connected [37]. In a (simple) neural network, the category to which MPL belongs, it is, therefore, possible to identify three components [38]:

- The input layer is responsible for receiving and processing input signals, adapting them to the requirements of the neurons in the network;
- The hidden layer which oversees the actual processing. The hidden layers can be more than one; the greater the number, the smarter the neural network will be;
- The output layer collects the processing results from the hidden layer and adapts them to the needs of the next layer-block of the neural network.

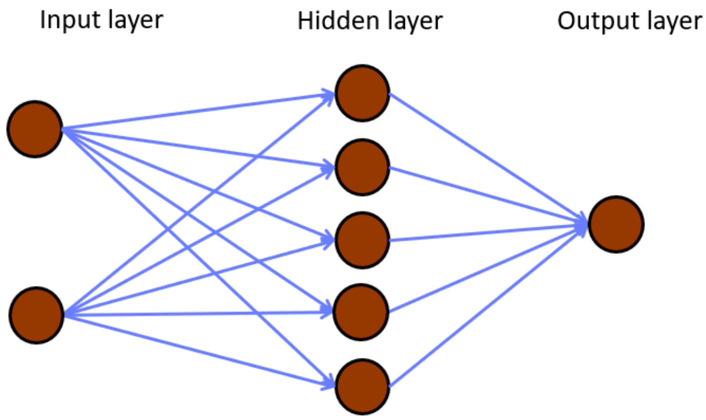

Figure 5. ANN architecture scheme.

Each layer of the neural network contains one or more artificial neurons, which in turn possess one or more input communication pathways, so-called dendrites [39]. In the basic artificial neuron model, a set of adaptive parameters known as weights are used to multiply the neuron's inputs. The sum of these weighted inputs is referred to as the linear combination of the inputs (Equation (1)) [40].

$$y = \left(\sum_{i=1}^{n} x_i * w_n \right) + b \tag{1}$$

Here,

- x_i = input;
- w_n = weights;
- b = bias;
- y = output.

Once the linear combination is calculated, the neuron takes the linear combination and submits it to an activation function, which, together with the linear combination, determines the neuron's output. As a result, the learning phase within the network takes place when the weights are adjusted to produce the correct outputs. The neural networks are often very large, with some containing hundreds of billions of weights, making optimization of all of them a challenging task that requires high computing power [41].

In feed-forward networks, each neuron at one level receives input only from neurons at earlier levels and can propagate only to neurons at later levels [42]. Thus, no self-connections or connections with neurons of the same level are possible. The main functionality of the neuron is therefore to propagate the signal through the network, with a flow of information from inputs to outputs [43]. In such a system, the current output depends solely and exclusively on the current input; therefore, in essence, the network has no memory of inputs that occurred at earlier times [44].

One limitation proposed historically by the scientific community concerns the supposed unfathomability of the final product. Indeed, it has been pointed out by several quarters that once an ANN has been trained, it is no longer possible to understand its exact operation and, consequently, risks losing control of one's product [45,46]. Today, it is possible to have an advanced broad understanding of the role of the various layers of the network and often of specific areas of each layer. To gain this understanding, the most effective strategy is to cast the network in reverse, entering the output and retracing the calculation until finding the exact input that would have generated that output [47]. This approach, combined with the ability to input not only the final output of the network but also intermediate outputs on each layer of the network, makes it possible to reconstruct the reasoning pattern of the network and identify the role of the various areas [48].

ANNs require substantial computing power. One solution is to distribute computations among several processors and perform those computations simultaneously. When training neural networks, the main ways to achieve this are model parallelism, which involves distributing the neural network among several processors, and data parallelism, which involves distributing training examples over several processors and processing updates to the neural network in parallel [49]. Although pattern parallelism allows training neural networks larger than a single processor can support, it usually requires adapting the model architecture to the available hardware. In contrast, data parallelism is model-independent and applicable to any neural network architecture. It is the simplest and most widely used technique for parallelizing neural network training [50].

The size of the available input data is another critical issue in ANN training. The amount of data required depends on many factors, such as the complexity of the problem. The unknown function that relates the input variables to the output variable takes a major weight in the choice of sample size [51]. However, it is also important to consider the complexity of the learning algorithm. In fact, the algorithm used to inductively learn the unknown underlying mapping function from specific examples becomes crucial in estimating the sufficient sample size to be used. It is necessary to have data sufficiently representative of the problem we are addressing. In addition, the data must be independent and identically distributed. We must have sufficient data to reasonably capture the relationships that may exist between both input features and output features [52].

3. Results and Discussion

3.1. Specimens Characterization

The samples made have different characteristics from the individual components (plaster and corn stem fibers). The matrix made of plaster is denser and more compact than the reinforced composite. As the percentage and length of fibers used for reinforcement increase, the density of composites decreases [53]. Adding fibers to the specimens increases their volume while reducing their mass, resulting in a decrease in composite density. However, if long fibers are used and the volume ratio is maintained, the arrangement of fiber bundles within the composite can create areas of high porosity, which further contribute to the reduction in the density of the specimens.

The characteristics of the composite produced from a plaster-based matrix are influenced by both the size of the fibers and the number of fibers added. Increasing the fiber content and length results in a decrease in the density of the reinforced material, with short fibers producing a denser composite than longer fibers. The use of long fibers can create areas of high porosity due to the constraints associated with fiber bundle arrangements, leading to reduced density of specimens at the same volume ratio. On the other hand, using shorter fibers increases compactness and thus the density of specimens by optimizing space occupancy. Numerous studies have indicated that composite materials exhibit improved mechanical properties, particularly in flexural and compression properties, especially in the phase following matrix failure [54–56].

Natural plant fibers are composed of crystalline cellulosic chains surrounded by a matrix of semicrystalline components like hemicellulose, pectin, and lignin. The high tensile strength of these fibers is an advantageous factor in enhancing fracture toughness and improving the behavior of gypsum products, particularly in reducing catastrophic failure. Depending on the raw materials used, the properties of calcium sulfate semihydrate may exhibit slight variations. The setting time of the material is mainly affected, which can result in significant differences in the microstructure of the cured material and, consequently, its mechanical properties [57]. In accordance with the above, the chemical composition of the corn stem essentially contains cellulose, hemicellulose, and lignin. In Table 4, the chemical compositions of some natural fibers usually used as reinforcement for composite production are shown.

Table 4. Chemical composition of corn stem [58–60].

Component	Corn Stem (%)	Jute (%)	Kenaf (%)	Flax (%)	Hemp (%)
Cellulose	30–40	65	70	72	60
Hemicellulose	30–40	12	20	20	20
Lignin	7–20	10	9	2	10

The water absorption rate in plaster–fiber composites can pose a problem due to the resultant changes in mechanical properties. The presence of cellulose in natural fibers increases the availability of free hydroxyl groups, which contributes to their ability to absorb water. Although the fiber itself is not soluble in water, it can absorb a significant amount of water through hydrogen bonds formed between the water molecules and the hydroxyl groups in the fiber components. This can cause considerable swelling, with the weight increasing by up to 200% of the original weight. This characteristic can also affect fiber adhesion to the plaster-based matrix.

Table 4 demonstrates that the cellulose content in corn stem fibers is low, resulting in reduced water absorption capabilities compared to other fibers. Surface treatment can effectively reduce the moisture absorption of natural fibers. Various studies have been conducted on chemical treatments applied to fibers intended for use as reinforcement. The most used treatments include acetylation, alkalinization, benzoylation, and silane treatment, which are all documented in the literature [61].

For this study, the fibers were subjected to a 24 h washing process with distilled water at room temperature (25 °C). This treatment effectively cleans the fiber surface by removing water-soluble organic compounds. It also enhances surface roughness, thereby improving fiber-matrix adhesion. Compared to other chemical methods, this treatment is less aggressive and more environmentally friendly. Recent studies have shown that washing with distilled water is more effective than other chemical methods such as treatments with ethylenediaminetetraacetic acid (EDTA) and sodium hydroxide (NaOH) [62].

3.2. SAC Measurements Results

In recent years, the acoustic properties of some natural fibers that are grown in Ecuador have been analyzed [25,63,64], hence the idea to study the acoustic behavior of corn cane, a product that is currently found in most of Ecuador's mountainous fields and in some coastal provinces. The main application of corn within the acoustic field is to exploit its absorption properties in a certain frequency range. Therefore, studies have already been carried out on some parts of this plant, such as the ear, the leaves, and the grain itself. In these studies, the absorption and frequency responses were determined by the impedance tube method [65]. Studies in which comparisons were made between natural fibers, with and without a binder, determined that additional materials or compounds, such as polymers, should be added to increase panel durability and functionality. These studies have allowed an improved adaptation of the microstructure of fiber with a binder, as it expands the performance of said material for its application as an absorbent panel [66]. The results obtained from this type of material determined that corn leaves or stems are efficient at medium and high frequencies. In addition, the use of corn stem fiber is considered renewable because it is a natural waste commonly called bagasse, which poses no harm to human health. According to Sari et al. [66], this type of fiber has close to 100 percent acoustic absorption at high frequency, fluctuating in the range of 1.6–3.2 kHz for fiber samples treated with 2 percent and 5 percent NaOH (sodium hydroxide) concentrates. This means that fibers that have been treated absorb more energy than purely natural fibers.

Based on the recent literature, we propose to develop absorbent panels based on corn stalks to evaluate acoustic behavior. To obtain a marketable product, corn stem fibers were added to a plaster-based matrix. Due to its low procurement cost, aesthetic finish, and easy workability and installation, plaster is one of the most widely used resources for interior finishes, siding, and walls in buildings.

To begin, the acoustic properties of specimens prepared as described in Section 2.2 were characterized through SAC measurements applying an impedance tube. Each specimen underwent multiple measurements, during which they were removed from the tube, then reinserted. This procedure served to ensure the minimization of any errors made during the measurement. During post-processing, any outliers were removed, and the measured results were averaged.

Figure 6 shows the results of SAC measurements for all two types of specimens made with different thicknesses. The addition of fibers reduced the density of the material and its surface hardness, thereby reducing its reflective properties. The mechanical properties were also reduced with the presence of fibers, which, however, cause the detachment effect to decrease in case of breakage.

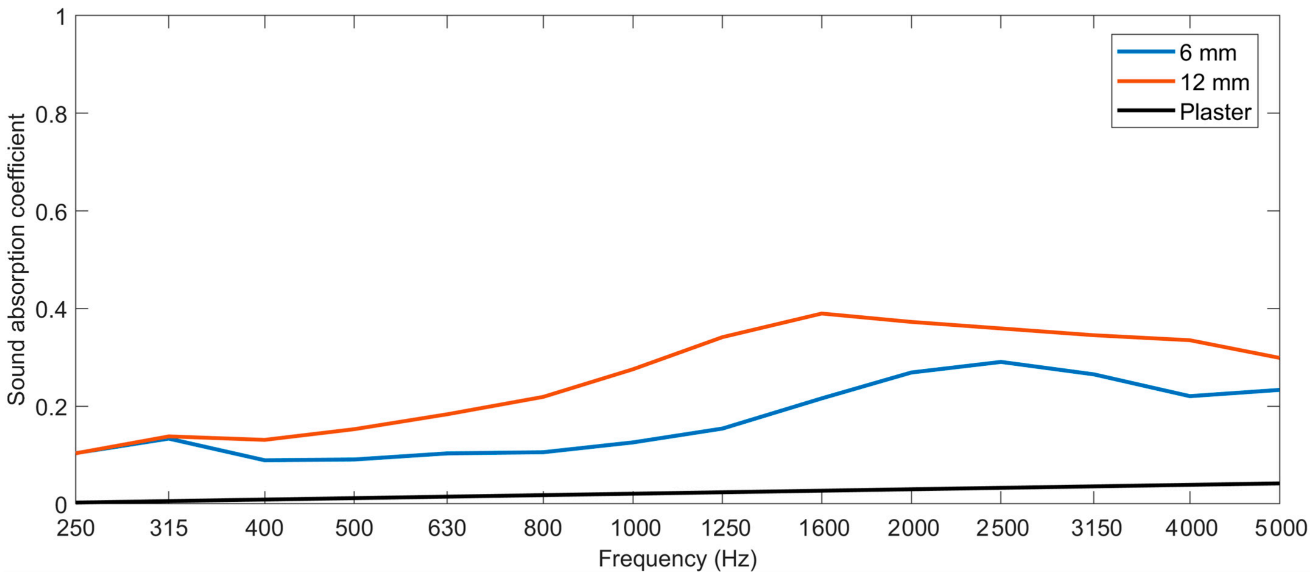

Figure 6. Results of SAC measurements in one-third octave bands. The two curves refer to the different specimen thicknesses (6 mm and 12 mm) and pure plaster.

Figure 6 shows the SAC trend in terms of frequency, in one-third-octave bands, on a logarithmic scale for the composite material with plaster matrix and reinforced with corn stem fibers. The SAC trend of the analyzed composite material is compared with the pure plaster-based binder. The addition of the reinforcing material not only improves the mechanical properties of the plaster but also significantly improves its acoustic properties. In fact, the porosity of the composite material is increased by the microscopic air pockets that are deposited on the surface of the corn stem fibers. This phenomenon is owing to the roughness and grooving of the fibers, which by opposing a frictional effect to the incident acoustic wave returns an increase in sound absorption. Attributable to the roughness of the fibers is also the increase in the damping capacity of the incident wave with a related increase in SAC.

Figure 6 also shows how SAC is affected by specimen thickness: increasing specimen thickness improves sound absorption capacity. This increase is particularly appreciated in the 400–1600 Hz frequency range. This is due to the path taken by the incident wave. In fact, since greater wavelengths correspond to these frequencies, sound absorption is more effective in the case of thicker specimens. The thicker the specimen, the greater the acoustic energy loss because of the expansions and contractions of the air molecules.

Table 5 shows the difference in the absorption characteristics between the reinforced material based on corn stem fibers and that obtained with other natural fibers derived from crop residues already available in the literature.

Table 5. Comparison of SAC values of composites reinforced with natural fibers.

Frequency (Hz)	Corn Stem	Sugar Cane [67]	Corn Stem	Sugar Cane [67]
	6 mm	6 mm	12 mm	12 mm
250	0.103	0.173	0.103	0.190
315	0.133	0.251	0.138	0.253
400	0.089	0.192	0.131	0.286
500	0.090	0.233	0.152	0.285
630	0.103	0.180	0.183	0.260
800	0.105	0.183	0.219	0.286
1000	0.125	0.387	0.275	0.466
1250	0.154	0.320	0.341	0.390
1600	0.216	0.408	0.389	0.409
2000	0.269	0.501	0.372	0.419
2500	0.290	0.585	0.359	0.445
3150	0.265	0.617	0.345	0.511
4000	0.220	0.548	0.335	0.476
5000	0.233	0.532	0.298	0.553

To better appreciate the comparison, the data in Table 5 are shown in the diagram in Figure 7.

The results obtained for the composite made from corn stem fibers show similar behavior to that made from sugar cane cultivation residues [67]. Figure 7 shows that the results of SAC measurement by the impedance tube method carried out on specimens of the same thickness made with a plaster matrix and reinforcement based on corn stem fibers and sugar cane fibers are comparable. The 12 mm specimen in particular shows that the curve relating to corn stem fibers lies just below that relating to sugar cane fibers. Near the frequency of 1600 Hz, they almost touch each other, while the curves become distant at the extreme frequencies. For the 6 mm specimen, a similar thing happens, only in this case, at high frequencies, the variance between the two curves still in favor of sugar cane becomes more pronounced. Corn stem fibers and sugar cane fibers have similar acoustic characteristics because they are physically similar when they dry out. The differences appreciated in the graphs in Figure 7 can be attributed to the quality of the fibers obtained because of the treatments. Fibers derived from sugarcane cultivation waste are rougher and thus when used as reinforcement in a plaster matrix composite create more cavities that make sound absorption more effective. Other studies have shown that sound absorption is affected by the arrangement of the fibers. Randomly arranged fibers improve their acoustic performance, while ordered fibers lower it. This is especially true at high frequencies [66]. Considering the results obtained, it is possible to state that this type of fiber could be used to combine with other binders to achieve an efficient response for the use of an environmentally friendly acoustic panel.

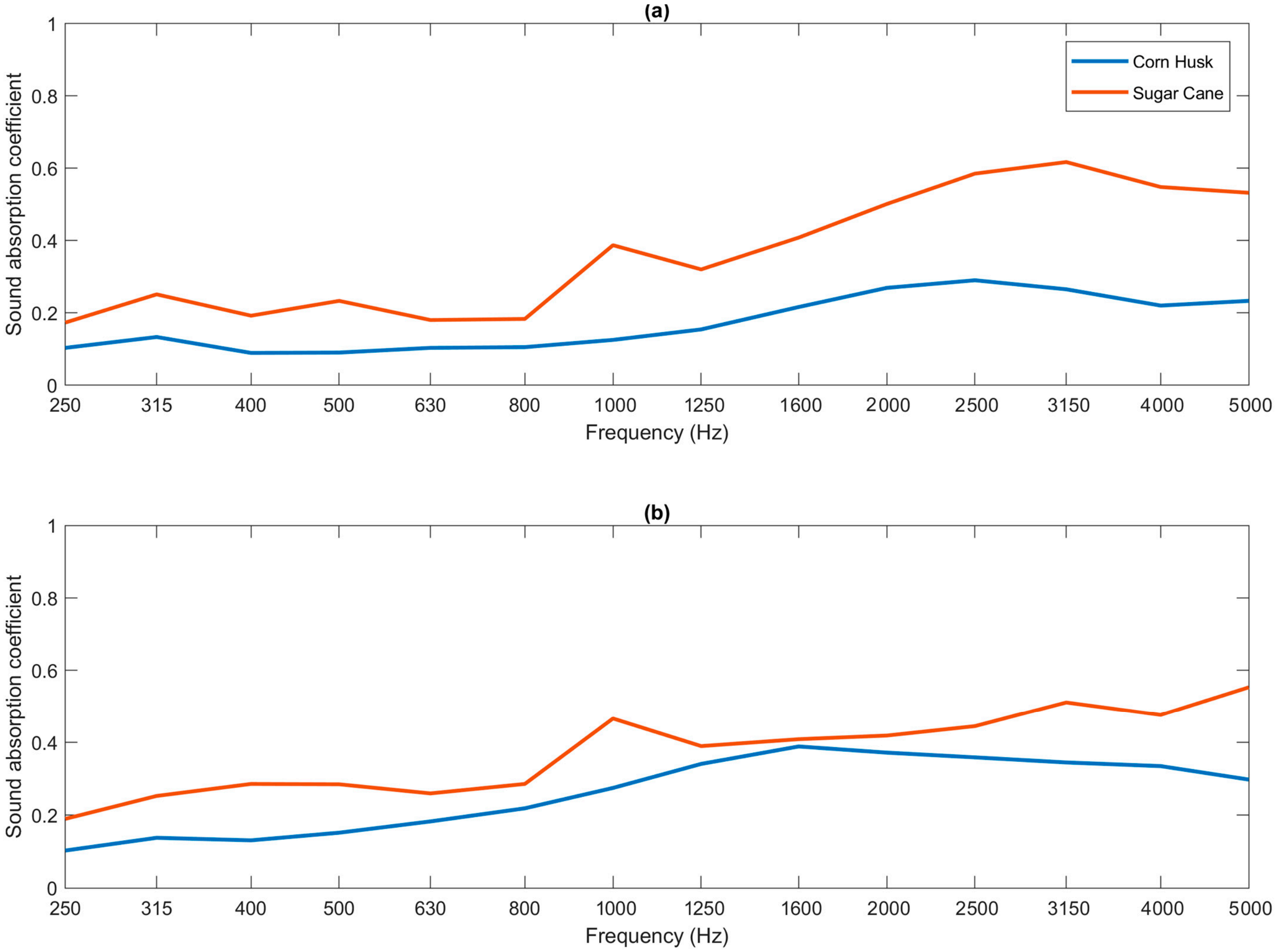

Figure 7. Comparison of SAC measurement results for plaster matrix and natural fiber-reinforced composite materials (corn stem and sugar cane). The curves refer to the different thicknesses of the specimens (6 mm and 12 mm); (**a**) 6 mm thick specimens; (**b**) 12 mm thick specimens.

3.3. ANN-Based Modelling

In recent years, several studies have used Machine Learning-based algorithms for SAC prediction [68–73]. Taking a cue from these, SAC measurements have been used to train a regression model for predicting material acoustic behavior based on ANNs. Figure 7 describes the architecture of the model.

The SAC prediction model formulated for corn stem fibers (Figure 8) involves two input features (frequency and thickness): frequencies in one-third octave bands (250 Hz to 5000 Hz) and thickness values of the two types of specimens made (6 mm and 12 mm). The prediction model returns as output the value of SAC in terms of frequency in one-third-octave bands relative to the thickness of the specimen. Since the output of the prediction model is numerical and continuous, we have confirmation that we are dealing with a regression problem with two predictors and one response variable.

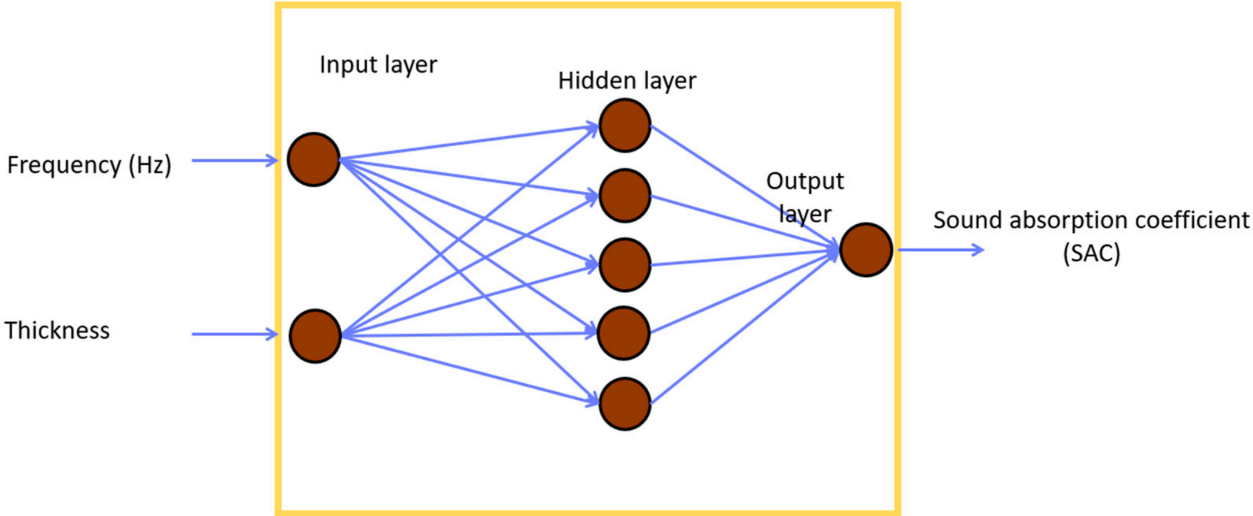

Figure 8. Architecture of simulation model of acoustic behavior of composite material reinforced with corn stem fibers based on ANNs.

The results obtained from the measurements of acoustic characteristics made with the impedance tube were stored in a data file with three columns: the following input variables (frequency and thickness) and the following output variable (SAC). In total, 2240 records were collected from the measurements, corresponding to the 14 one-third octave frequencies in the range of 250–5000 Hz, the two thicknesses of the specimens (6 mm and 12 mm). To apply a prediction algorithm based on supervised learning, it was necessary to provide the labeling procedure [74]. This procedure was carried out by associating the value of the SAC, obtained from measurements with the impedance tube, with the thickness of the specimen at the specific frequency [75]. Labeling is crucial in a methodology centered on supervised ANN. Using labels, it is possible to train the model using a subset of data by specifying the desired output, so that, at the end of the learning process, the model can generate the correct label by providing only a subset of the input data [76].

An ANN-based model of the feed-forward type was developed for SAC prediction. For training the network, the Bayesian regularization backpropagation algorithm was applied [77,78]. The Bayesian Regularization method deals with the problems of training and generalization of a network in a statistical way. Given a neural network trained with a training set, it is computed which is the most likely output vector, for a given input vector, not belonging to the starting training set. In this way, it is possible to train a network several times always obtaining good results, but different each time with weights. This is due to the random procedure by which the weights are initialized at the beginning of each training session. In the classical optimization approach typical of the ANN training phase, all this is ignored, whereas, in the Bayesian approach, all solutions are combined to find the one that produces the best generalization. The SAC prediction algorithm was built using Mathworks' Matlab (2022) platform [79].

SAC measurements were then divided into two datasets: 80% of the data was used for ANN training, and the remaining 20% was exploited for the testing phase. Figure 9 shows the gradient and mean squared error values during the training phase.

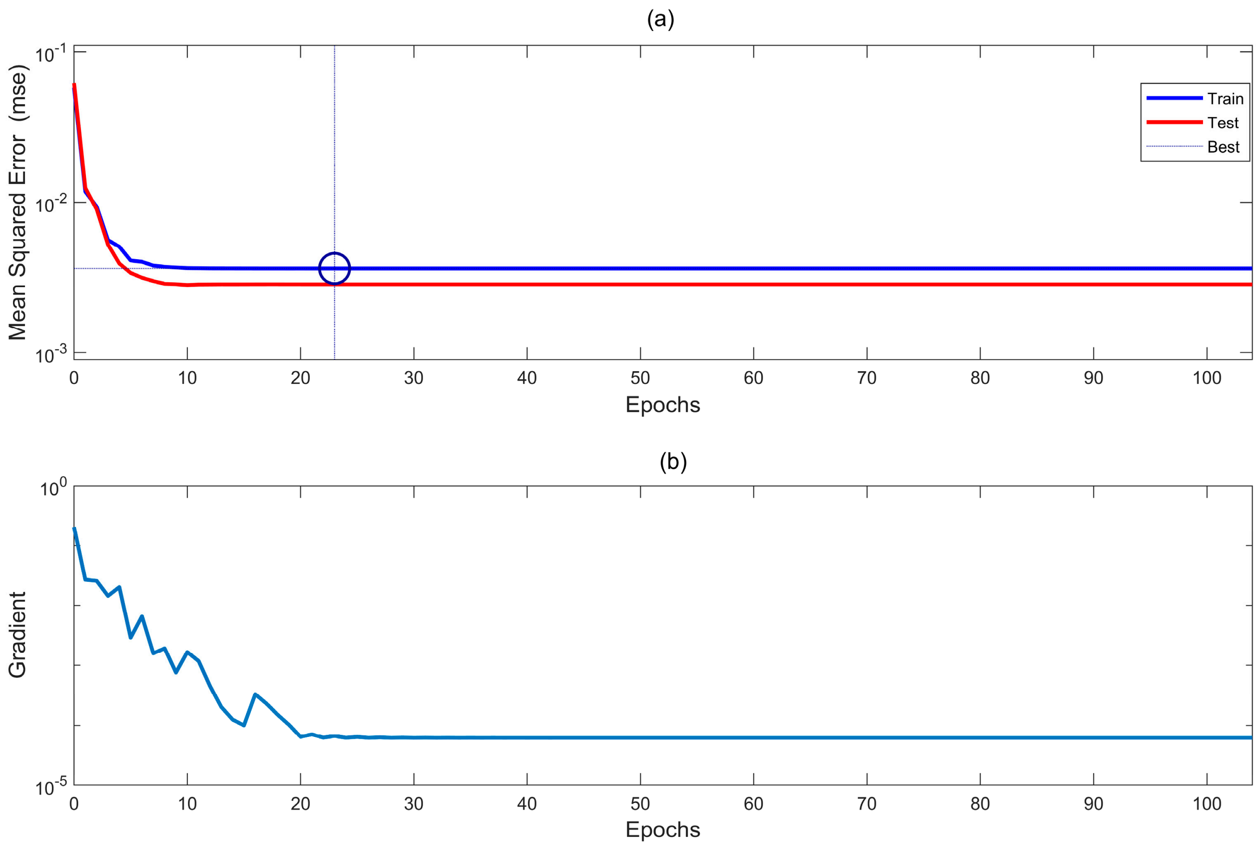

Figure 9. Progress of training phase performance: (**a**) mean squared error of training and test phase (MSE); (**b**) gradient evaluation.

Table 6 shows the values of some parameters at different stages of the iterative cycle.

Table 6. Progress of some training parameters.

Parameter	Initial Value	Stopped Value	Target Value
Epoch	0	104	1.00×10^{3}
Performance	0.057	0.00361	0
Gradient	0.204	6.17×10^{-5}	1.00×10^{-7}

Two evaluation metrics were used to evaluate the performance of the simulation model: the MSE calculates the difference between the actual data and the data predicted by the model by evaluating the dispersion in the data. It evaluates the distribution and concentration of the measures around a central tendency [80]. The correlation coefficient, on the other hand, ranges from −1 to +1. A value of −1 or 1 indicates a perfect correlation between the variables, while 0 indicates no correlation. A positive correlation means that the high values of one variable correspond to the high values of the other, and vice versa for low values [81,82].

The results returned by the SAC prediction model evaluated according to the adopted metrics are shown in Table 7.

Table 7. Performing evaluation of the ANN-based model.

	Observations	MSE	R
Training	1792	3.61×10^{-3}	0.8451
Test	448	2.83×10^{-3}	0.8836

The model's capability to fit the measurement results can be assessed visually using scatter plots, in which measurement values are plotted on the horizontal axis (target) and predicted values are plotted on the vertical axis (response).

Figure 10 presents the graphical indicators of the points near the solid line representing the optimal situation, demonstrating the accuracy of the model predictions. To evaluate the absorption capability of the corn stem fibers, we compare the trend of SAC with the frequency of the measured versus simulated data (Figure 11).

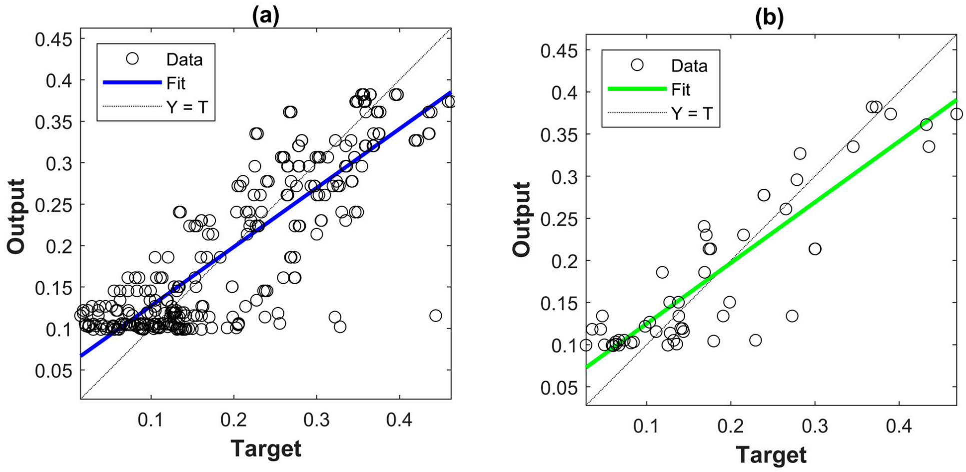

Figure 10. Model output versus target value for training phase (**a**) and testing phase (**b**).

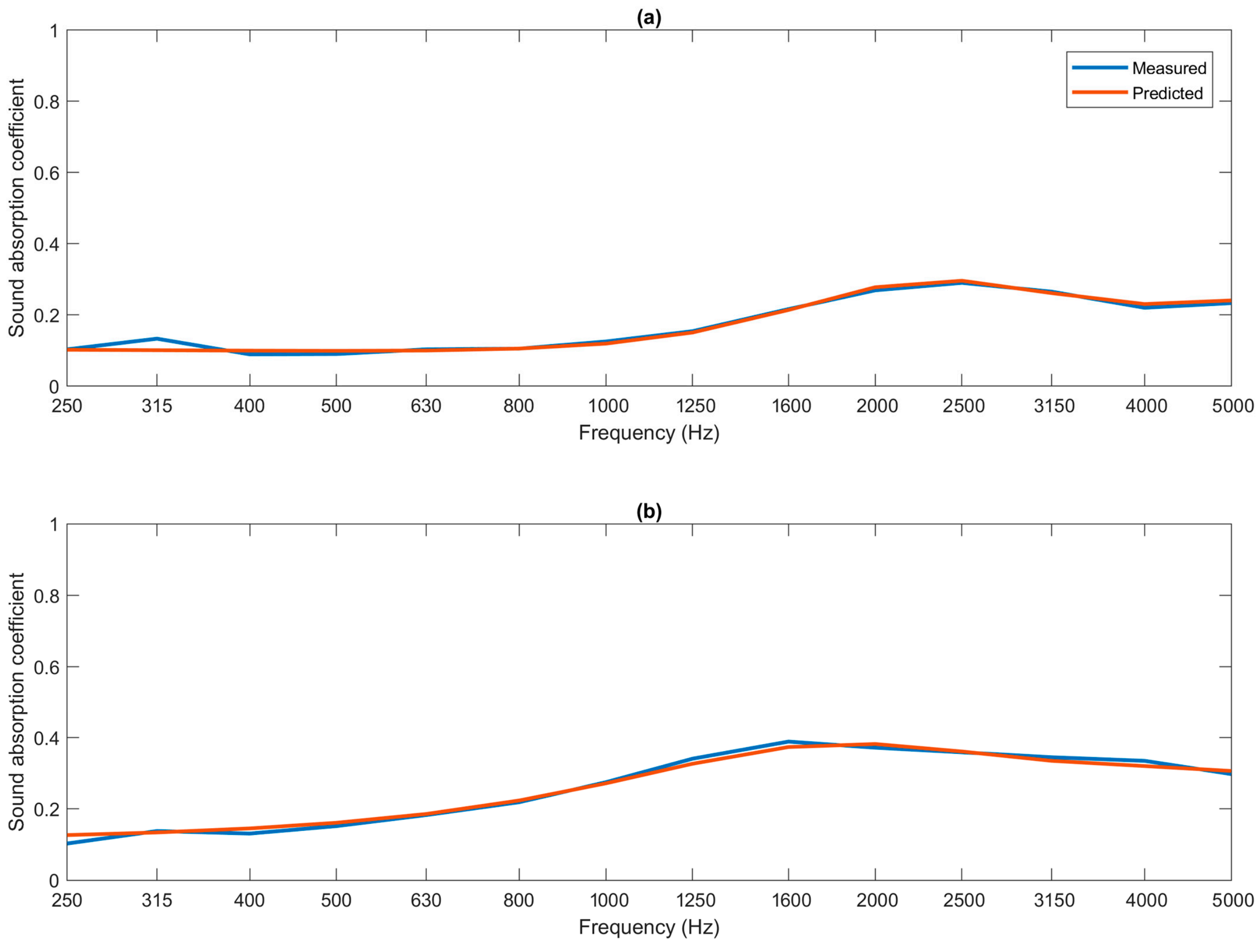

Figure 11. Measured versus predicted SAC data: (**a**) 6 mm specimen; (**b**) 12 mm specimen.

Figure 11 shows that the ANN-based model has good simulation capability, as the measured and predicted values are similar to other studies available in the literature [83,84]. In addition, the simulated data curve effectively fits the measured data and corrects for the anomalies present in Figure 6 at low frequencies.

4. Conclusions

This work examined the characteristics of corn fibers as a reinforcing material for creating a plaster matrix composite with possible use as an acoustically absorbent material. Fibers extracted from corn crop residues were mixed with a binder to create panels of two thicknesses of 6 mm and 12 mm. The SAC of the samples was then measured according to the UNE-EN ISO 10534-2 standard. In addition, a simulation model founded on ANN was used to predict the sound absorption coefficient and compare the results with experimental data. The simulation model effectively matched the experimental data and corrected any low-frequency anomalies.

After comparing the results obtained from the measurements of the Sound Absorption Coefficient (SAC) with the impedance tube and the ones from the Artificial Neural Networks (ANNs) model, it was observed that the model exhibited good simulation capability. The ANNs model highlighted the following aspects:

- The simulated data curve effectively adapted to the measured data, demonstrating the capacity to correct anomalies highlighted in the low-frequency range;
- For thicker samples of 6 mm, a deviation was observed between the measured and predicted data at the low frequencies;
- Throughout the frequency range, the predicted data consistently lay below the measured data.

The ability to predict the SAC by applying this ANN model allows for the acoustic performance of a material to be evaluated in any configuration, saving resources and eliminating the need for additional acoustic measurements. The model's good performance suggests its use for simulating the acoustic behavior of the material.

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