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Article

Comparative study of computational models for reducing air pollution through the generation of negative ions

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Abstract: Today, air quality is one of the global concerns that governments are facing. One of the main air pollutants is the particulate matter (PM) that affects human health. This article presents the modeling of a purification system by means of negative air ions (NAIs) for air pollutant removal, using computational intelligence methods. The system uses a high voltage booster output to ionize air molecules from stainless steel electrodes; its particle-capturing efficiency reaches up to 97%. With two devices (5 x 2 x 2.5 cm), 2 trillion negative ions are produced per second, and the particulate matter (PM 2.5) can be reduced from 999 to 0 mg / m3 in a period of approximately 5 to 7 minutes (in a 40 x 40 x 40 cm acrylic chamber). This negative ion generator is a viable and sustainable alternative to reduce polluting emissions, with beneficial effects on human health.

Keywords: Environmental pollution; air purification; negative ion generators; particulate matter.

1. Introduction

Both developing and developed world cities are at a crossroads in making the right decisions to ensure a sustainable future [1]. The increasing pollution levels in cities and their serious effects on human health make it essential for governments to take immediate action to combat the consequences of human exposure to low-quality air [2]. Studies have shown that, environmental pollution through particulate matter causes different health problems such as respiratory and heart diseases [3] - [9].

Within particulate matter, special attention has been paid to particles with an aerodynamic diameter of 2.5 μm (PM 2.5), given their chemical composition and the threat to produce lung diseases [10]. Consequently, PM 2.5 has become a source of major concern worldwide [11]. Different studies indicate that the composition of particulate material varies according to the emission source [12], and that the presence in the atmosphere of this pollutant causes a variety of impacts on vegetation, the environment and human health [2], [11], [12].

Recently, different techniques and applications have been studied as solutions to air purification, especially in indoor spaces [15]; along which semiconductor photocatalysis [15], [16] [17], oxidation with ozone [18] stand out; there is also [19], filtration [20], use of adsorbents [21], plasma [22], ultraviolet [23], generation of ions and plasma [24], among others. It is highlighted that alternative filtration technologies based on electrostatic precipitators or negative ion generators have gotten more attention in the academic field due to a lower noise level, lower electricity consumption, lower maintenance cost and higher cleaning energy efficiency [25].

Regarding the use of air ionization for removing polluting particles, the use of Corona Effect Discharge technology is highlighted [26], [27]. Indoor air enhancement with negative ions provides air purification results with superior efficiencies [28], [29]. The research conducted by Nadali et al. [14] concluded that negative ions charge particles by producing a strong electric field in such a way that it the causes movement of charged particles towards interior surfaces, which finally settle on the surfaces of the walls and the floor. Guo et al. [30] demonstrated that particulate matter (PM 2.5) in a closed glass chamber (5,086 cm3) decreases rapidly from 999 to 0 µg m - 3 in 80 seconds under an operating 0.25Hz TENG device frequency. Sawant et al. [31] showed that the negative ion system removed between 93% and 97% of the fog or smoke particles in 6 minutes, in a glass chamber (60 cm x 30 cm x 40 cm). Additionally, Pushpawela et al. [32] highlight the use of negative ions for removing fine PM 2.5-type particles and eliminating cigarette smoke [28].

This article presents the modeling of a system for air purification through the generation of negative ions for the removal of PM 2.5 particles. For this, a simulation is carried out by means of three computational intelligence systems: The Artificial Neural Networks (ANNs), the K-Nearest Neighbors (k-NN) or K-neighbors and the Vector Support Machine (VSM). These three methods are implemented in order to identify the computational system that best responds to the air purification process behavior prediction by means of negative ions using three different pollutants (Gasoline, cigarette and incense).

2. Materials and Methods

This research is based on knowledge of the effect on negative ions applied to a controlled 40x40x40 cm environment, in order to identify the level of air decontamination using three types of pollutants. The obtained data were processed and analyzed in order to compare the computational models' performance that allow estimating the operation of an ionization air purification system. Figure 1 describes the different phases of the process.

Figure 1. Proposed methodology workflow.

2.1. Air purification system through negative ions

Air ionizers are a kind of air purifier that is based on the generation of ions by applying an electric field between two metal electrodes of unequal curvature radius. The ions are accelerated by the electric field and, thanks to the collisions of neutral ions, the momentum is transferred from the ions to the neutral molecules, thus creating an ionic effect that can be used to purify the air: the dust and the particles suspended in the ambient collect the electrons as they cross the discharge area. These negatively charged particles then settle on grounded surfaces. Figure 2 presents the air purification process by means of negative ions.

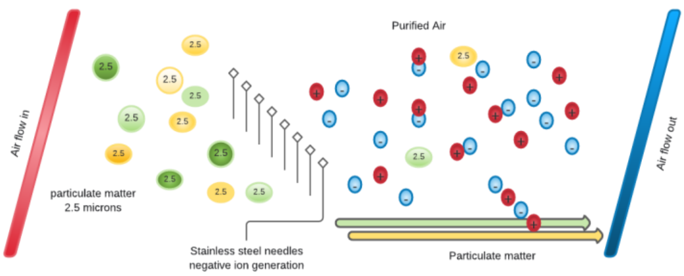

Figure 2. Configuration of the negative ion air purification system

The generation of negative ions is favored by the so-called "Corona Effect" [33]. When a high negative voltage is applied to a conductor or electrode, and the generated

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electric field is high enough, a corona discharge occurs [12,13]. If a charged conductor or electrode has a type of needle with a sharp tip, the electric field around the tip will significantly be higher than elsewhere, and the air near the electrode can ionize and generate negatively charged particles [34]. The intensity of the corona discharge depends on the shape and size of the conductors, as well as the applied voltage. An irregularly shaped conductor, especially with a sharp tip, results in more corona discharge than a smooth conductor and, large diameter conductors produce a lower corona discharge than small diameter conductors; the higher the applied voltage, the more negative ions are generated [34]. The closer the distance to the corona point, the higher the concentration of negative ions is detected, since the continuous generation of negative particles by corona discharge is related to a chain reaction process called electron avalanche [33]. This process requires the design of a voltage multiplication system, which is described below.

2.1.1. System design Voltage multiplier

The ion generation system is a voltage multiplier system which is divided into stages, made up of two diodes and two capacitors for each stage, plus an alternating voltage input. The operating principle of this system is the successive charging of capacitors due to the diode-cascade enabling; each diode presents voltage loss given by the technical characteristics of the component, obtaining at the output of each stage twice the input minus the loss' value. In order to obtain higher values in the output voltage, the described steps are replicated, as illustrated in Figure 3.

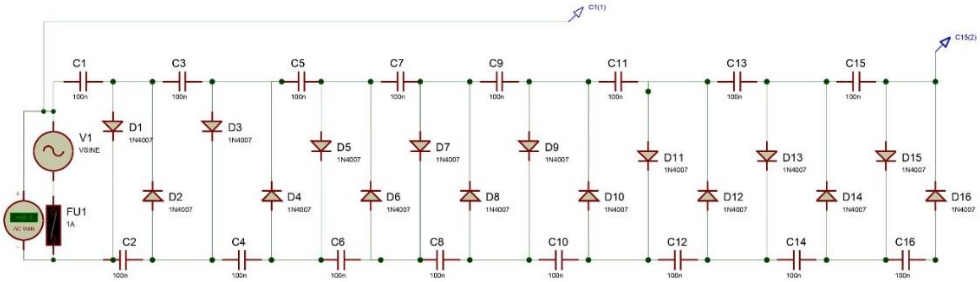

Figure 3. Voltage multiplier circuit.

Using Kirchoff's laws for the analysis of voltage multiplier circuits as described in figure 2, it can be verified that:

$$V_o = -nV_{i,RMS} \tag{1}$$

Where Vo is the output voltage of the multiplier circuit, n is the number of multiplication stages, and $V_{i,RMS}$ denotes the input voltage's effective value applied to the circuit [35]. Taking into account this configuration, the calculations to design a voltage multiplier are carried out, this will conduct the necessary tests. The designed system is tested in simulation, and the Proteus software is used to identify the system's output response and validate the voltage levels produced by it.

Figure 4 presents the simulated response of the voltage elevation system for the generation of negative ions. It shows the descending curve that is generated as the voltage circulates through the stages of the voltage multiplier until it reaches the stability point corresponding to -7,500vdc. In this way, the negative ions required for the purification process are generated.

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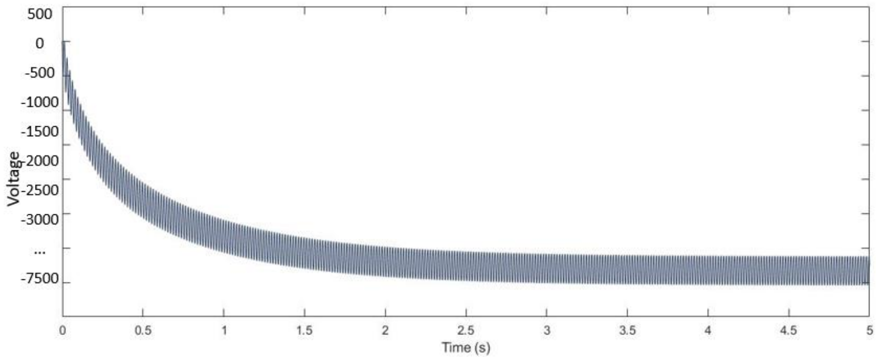

Figure 4. Response of the voltage multiplier system

The designed voltage multiplier circuit is put into a practical assembly, with stainless steel emitting needles (electrodes) used as an interface between the electronic circuit and the environment for the transfer of the generated negative ions. With the system, a voltage increase of 441V per cycle is achieved, which leads to obtaining a voltage at the circuit's output -7500V at 10mA, with a total 10 trillion ions / second generated and transferred to the environment through the emitting needles arranged at the circuit's exit.

2.2. Computational modeling of the PM 2.5 particles reduction through ionization.

In order to determine the model that best fits the air purification system with negative ions applying pollutants such as gasoline, cigarettes and incense, the experimental data from the PM 2.5 concentration level are collected; it is sought to approach this variable's behavior through the implementation of three computational modeling systems, namely: The artificial neural network (ANN), the K-Nearest Neighbors (KNN) artificial intelligence system and the Vector Support Machine (SVM) system.

2.2.1. Artificial Neural Networks (ANN)

An ANN is made up of a large number of interconnected units called neurons, which have a certain natural tendency to learn from the information in the outside world [36]. This type of network provides solutions to specific problems by means of a training process. Through it, the network learns from its errors and a model is obtained from that. It describes the studied phenomenon as accurately as possible [37].

In general, ANN models are used as very powerful machine learning algorithms for time series prediction of different engineering applications. The ANN model consists of an input layer, hidden layers, and an output layer. Each hidden layer has weight and skew parameters to manage neurons. To transfer the data from the hidden layers to the output layer, the activation function is used. Learning algorithms are used to select the weights within the neural network structure. The weight selection is based on performance measurements such as the mean square error (MSE).

2.2.2. The K-Nearest Neighbors (KNN) Model

The KNN algorithm is one of the traditional machine learning algorithms used for data classification [38]. KNN algorithms use K neighbor values to find the closest point between objects. The K value is used to find the closest points in the feature vectors and the value must be unique. In this research's algorithm, the Euclidean distance function (Di) was applied to find the closest neighbor in the feature vector, where x1, x2, y1 and y2 represent the input data variables.

$$D_i = \sqrt{(x_1 - x_2)^2 - (y_1 - y_2)^2} \quad (2)$$

2.2.3. Vector Support Machine (SVM)

The SVM is a learning method with theoretical backgrounds in statistical learning theory [39]. The SVM was originally developed to perform classification tasks but later, it has been widely used to solve regression problems; a method called Support Regression Machine (SVR). The SVM produced model only depends on a subset of the training data because the cost function to build the model takes into account the training points that are beyond a defined margin value. Similarly, the model produced by the SVR only depends on a subset of the training data because the cost function to build the model ignores any training datum that is close (within a ε threshold) to the model's prediction.

2.2.4. Model performance measuring

Performance measurement approaches, such as the Root Mean Square Error (RMSE) and the Mean Absolute Error MAE were applied to evaluate the ability of the proposed models to predict the decrease in the Pm 2.5 concentration due to the negative ions effect on the test environment. The RMSE is calculated from the sum of the individual squared errors. The MAE involves the sum of the errors' magnitudes (absolute values) to obtain the 'total error' and, to divide by the number of errors [40]. The statistical methods used are defined as follows:

- Root mean square error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(y-\hat{y})^2}{N}} \quad (3)$$

- Mean absolute error (MAE):

$$MAE = \sum_{i=1}^{N} \frac{|y-\hat{y}|^2}{N} \quad (4)$$

Where y is the observed experimental data, and $\hat{y}$ represents the data estimated by the model, and N denotes the total amount of data.

3. Results

3.1. Design of the experiments and data collection

The experimental setup is based on the knowledge of the effect of negative ions applied to a 6400 cm3 cubic-shaped container with the electrodes of the voltage multiplier system for generating negative ions, in contact with the container's atmosphere. In this system, the input air is injected with pollutants such as gasoline, cigarettes and incense; these mostly contain PM 2.5 particles and volatile organic components (VOC), namely:

- Gasoline: carbon dioxide, nitrogen oxide, carbon monoxide, and hydrocarbon molecules
- Cigarette: nicotine, tar, arsenic, lead, polyaromatic hydrocarbons, and
- Incense: carbon monoxide, sulfur dioxide, nitrogen oxide, and formaldehyde

This air is brought into contact with the negative ion generator using high voltage applied to sharp emitter points generating an electric field. In this way, the contaminating particles bind with the negative ions generated taking an excessive weight and adhering to the test surface. Negative ions also cause particles to be attracted to stainless steel needles and the ion-generating electrodes to produce a high density of negative ions (20 trillion ions per second) in two sets used for testing [41]. As a result, cleaner and more purified air is produced at the system's output. During this process, the measurement of parameters such as the quantity of the generated ions, the concentration of particulate matter suspended in the air with a diameter less than 2.5 microns (PM 2.5), the concentration of volatile organic compounds (TVOC), the concentration of formaldehyde or methanal (HCHO), RH and the temperature are performed; this, in order to obtain the necessary experimental data to execute the comparison of computational models representing the process.

3.1.1. Design of the experiment

In order to know how the air purification process by means of negative ions works, and to determine the impact of the variables affecting the process, the 2 ^ k Factorial design of experiments was performed in the Minitab software. Factorial designs are widely used in experiments that include several variables when it is necessary to study the overall effect of factors on a response. The 2 ^ k Factorial design is the most widely used because the factors have only two levels, which can be quantitative or qualitative [42]. This design allows exploring a chosen area of the experimental domain; it also allows finding a promising direction for further optimization [43].

The selected experimental design corresponds to the 2 ^ k series which has four factors, Ions, Gasoline, Cigarette and Incense, as independent variables. Each one is run at two levels. This design is called a 2 ^ 4 factorial design. The main objective is to evaluate the impact of these factors on the amount of particulate matter (PM 2.5) present in the environment but also, on measuring HCHO and TVOC. The levels of the factors can be called low and high. In this particular case, the level selection, in this particular case, indicates that it is applied (high, value 1), or that the factor is not applied (low, value -1).

After processing the data for the 2K factorial design of experiments using the Minitab software, a reliability of 77.04% is evidenced for the influence of the factors on the amount of 2.5 microns particulate matter of. On the other hand, the execution of the pollutant measuring tests HCHO (38.97%) and TVOC (58.05%) is excluded. This is since the design of experiments' reliability percentage is less than 60%. The low level of reliability for HCHO and TVOC is attributed to the low number of repetitions in the experiment (considering that the higher the number of repetitions the influence of human error in the sampling is minimized). Figure 5 illustrates the impacts of the presence (1) and absence (-1) of the design of experiments' factors on the concentration of PM 2.5 pollutant.

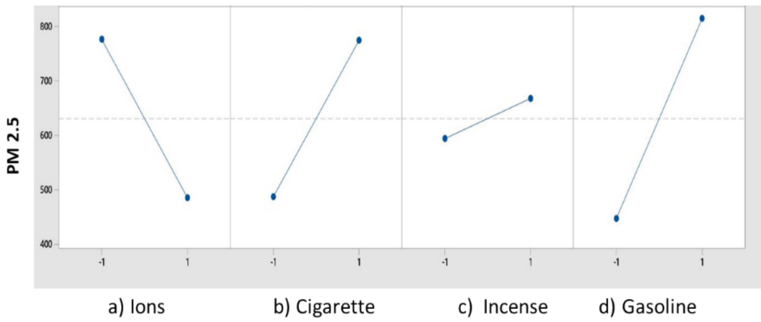

Figure 5. Main effects of the presence (1) and absence (-1) of the design of experiments' factors on the concentration of PM 2.5 pollutant.

It is possible to determine that particulate matter decreases when negative ions are present in the environment (Fig. 5a); for cigarette (Fig. 5b) and gasoline (Fig. 5d) pollutants, the slope is steeper, which allows identifying that they are pollutants with the greatest impact on the environment. Meanwhile, by using incense (Fig. 5c) as a pollutant, it is identified that it increases the particulate matter, but the contamination slope is lower with respect to cigarettes and gasoline. This shows the profound impact that the generation of negative ions offers to the reduction in the concentration of PM 2.5 in the test environment; this indicates their role as a reducing agent for this type of pollutant.

On the other hand, figures 6 to 8 show the variation in the concentration level of the particulate material PM 2.5 in the presence of each pollutant independently, and the effect of increasing the concentration of negative ions.

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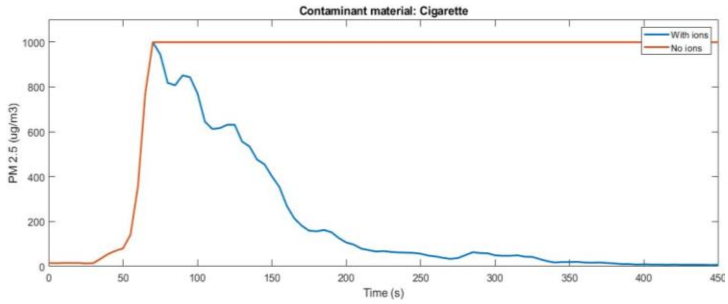

Figure 6. Concentration of PM 2.5 caused by the contaminant Cigarette (Orange) and the effect of the presence of negative ions (blue)

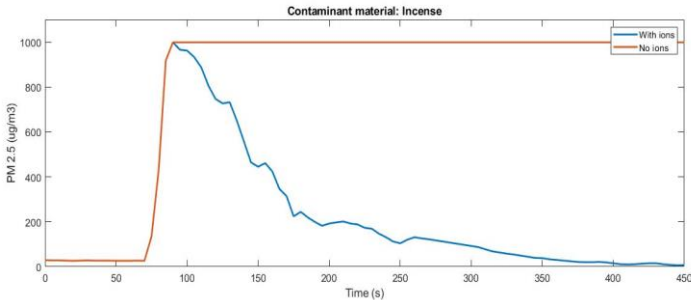

Figure 7. Concentration of PM 2.5 caused by the contaminant Incense (Orange) and the effect of the presence of negative ions (blue)

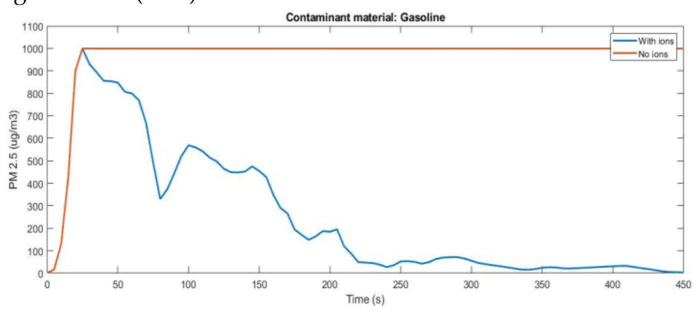

Figure 8. Concentration of PM 2.5 particulate material caused by the contaminant Gasoline (Orange) and the effect of the presence of negative ions (blue)

For all pollutants, the PM 2.5 concentration reached the sensor's maximum measurement saturation level (around 1000 ug / m3), although for gasoline, it does so in half the time it takes for cigarettes and incense. Once this level of saturation is reached, the negative ion generation system comes into action, and it is immediately observed that the concentration of PM 2.5 decreases, taking between 3 and 4 minutes to reach zero.

3.1.2. Comparison of the obtained computational models

The experimental data were processed using the MATLAB 2020 tool, and algorithms were implemented to generate computational models that allow estimating the reduction in the concentration of PM 2.5 from the presence of negative ions for each of the pollutants analyzed. In each case, the following techniques were used: The artificial neural network (ANN), the K-Nearest Neighbors (KNN) artificial intelligence system, and the Vector Support Machine (SVM) system.

The responses simulation was carried out using a computer system with an i5 processor and an 8 GB RAM to process all the required tasks. Each model was identified using 70% of the data for training and the remaining 30% for validation.

Figures 9, 10 and 11 show the comparison among the experimental data and the obtained computational models from each technique to estimate the concentration of PM 2.5 in the presence of negative ions for the contaminants Cigarette, Incense and Gasoline. The figures show that the estimated computational models captured the behavior trend of the observed concentration, where the x-axis represents time in seconds and the y-axis the PM 2.5 data. It can also be observed that the estimation with the SVM method in all cases ended up reaching negative values, which are not plausible for the real behavior of the estimated variable.

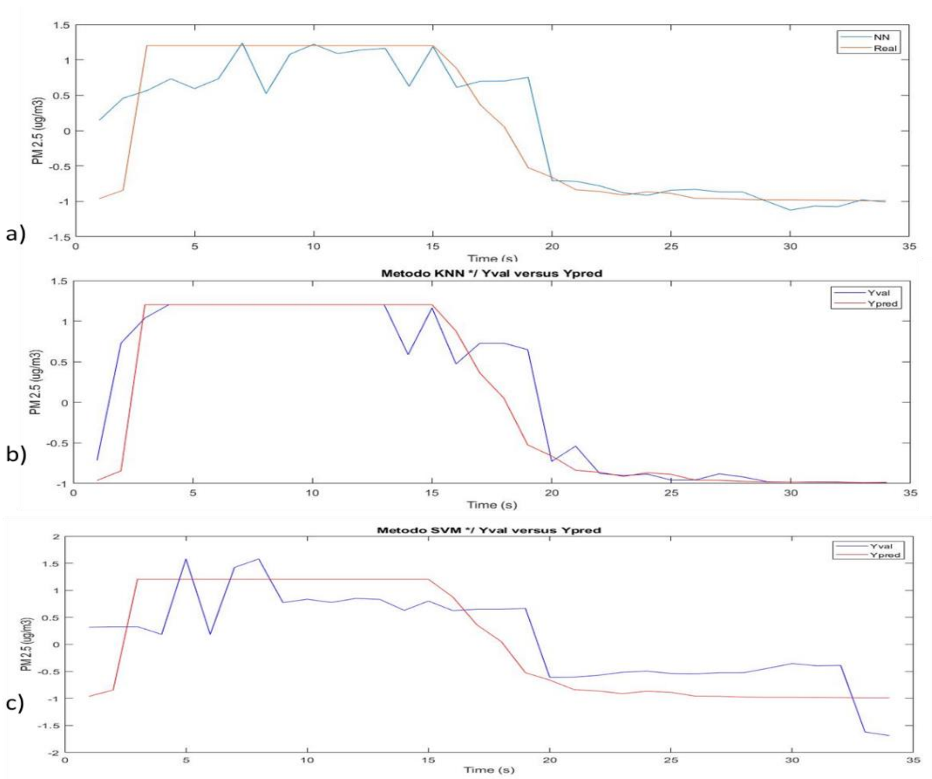

Figure 9. Comparison of the computational models for estimating the concentration of PM 2.5 caused by the cigarette pollutant with the ANN (a), KNN (b) and SVM (c) techniques.

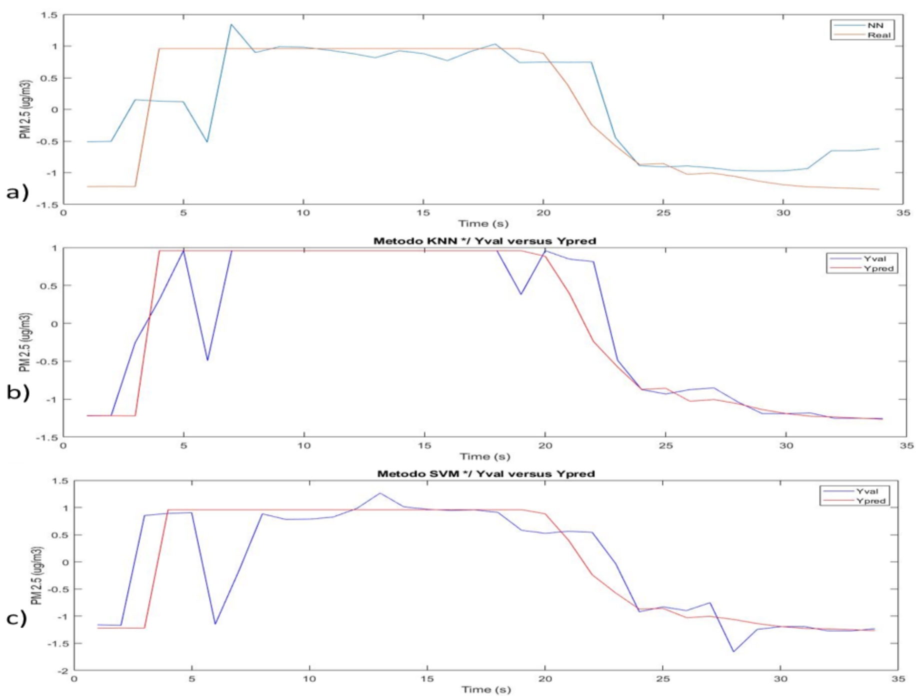

Figure 10. Comparison of the computational models for estimating the concentration of PM 2.5 caused by the Incense pollutant with the ANN (a), KNN (b) and SVM (c) techniques.

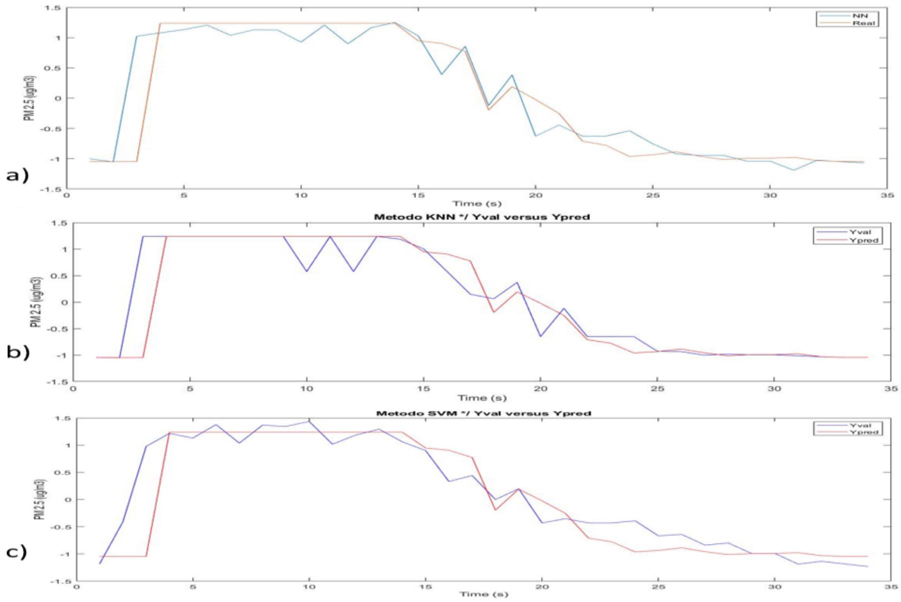

Figure 11. Comparison of the computational models for estimating the concentration of PM 2.5 caused by the Gasoline pollutant with the ANN (a), KNN (b) and SVM (c) techniques.

In order to analyze the different obtained models' performance for the estimation of PM 2.5 in the presence of negative ions, the RMSE (Root Mean Square Error) and the MAE (mean absolute error) metrics were used. These prediction errors can help determine how the expected values deviate from the values observed in the experimentation.

Table 1 summarizes the prediction results obtained by each of the models during the training and testing phases. According to the evaluation metrics (RMSE and MAE), the values estimated by the prediction models were very close to the experimental ones. In all the cases evaluated, the models obtained with the SVM technique reached the highest levels of error, being the model for the contaminant Incense, the one that presented the highest amount of error according to the metrics used. On the other hand, the model with the closest approximation and best response in estimating each pollutant corresponds to the one obtained using the KNN technique.

Table 1. Error result of the applied computational intelligence methods.

Pollutant	Methodo	RMSE Error	MAE Error
Cigarette	ANN	0.3957	0.1915
	KNN	**0.3906**	**0.1733**
	SVM	0.4746	0.2594
Incense	ANN	0.4758	0.4511
	KNN	**0.3900**	**0.1718**
	SVM	1.1167	0.5616
Gasoline	ANN	0.4636	0.2426
	KNN	**0.4615**	**0.1925**
	SVM	0.5298	0.4092

According to the data and the procedure performed, the KNN technique is the best method to represent the reduction in the concentration of PM 2.5 in the presence of negative ions for the Cigarette, Incense and Gasoline pollutants. The developed model can easily and economically be used to predict the effectiveness of the generation of negative ions in air decontamination processes and, therefore, guide the development of effective strategies for better sustainability and air quality management through the removal of particulate matter.

4. Conclusions

Modeling and predicting the effectiveness of air decontamination methods using computational algorithms is an important action for environmental protection. Computational models were developed to predict the impact of negative ions on the reduction of particulate material PM 2.5 in the environment by using the data obtained in an experimental setup, using a designed ionization system and setup. The development of new methodologies using advanced algorithms inspired by artificial intelligence techniques can help in the evaluation of strategies to improve the quality of the environment. In the proposed methodology, artificial neural networks (ANN), K-Nearest Neighbors (KNN) and Vector Support Machine (SVM) algorithms were used to predict the concentration decrease, and its performance was statistically assessed. The following conclusions can be drawn:

The present study explored alternative artificial intelligence methods to predict the reduction in particulate matter PM 2.5 from experimental data from a test setup in a 6400 cubic-centimeter container. The proposed experimental design allowed obtaining the data for the implementation of artificial intelligence models to predict the effects of negative ions in the reduction of PM 2.5 generated by contaminants such as cigarettes, incense, and gasoline.

Secondly, computational models can be developed by using the Artificial Neural Networks (ANN), the K-Nearest Neighbors (KNN) and the Support Vector Machine (SVM) to predict the reduction of PM 2.5 concentration in the air. Particularly, the prediction values were very close to the observation values for the different methods and contaminants. The prediction results with the KNN technique were superior to those generated from ANN and SVM.

In addition, this research confirms that negative ions are an effective method and a promising option for improving environmental quality, which can be implemented to reduce pollution due to the presence of 2.5-micron particulate matter in the air. The robustness and efficiency of the proposed methods for predicting the effectiveness of negative ions in air decontamination can be examined in future work. The models developed can be implemented to predict the efficiency of strategies to improve air quality in closed spaces, contributing to environmental sustainability. Also, a future work could be the implementation of these methods in open space environments.

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Conflicts of Interest: The authors declare no conflict of interest.

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