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Passengers' Comfort Modeling Inside Aircraft

A. Brindisi* and A. Concilio†
Centro Italiano Ricerche Aerospaziali, 81043 Capua, Italy

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This paper introduces the approach for modeling passengers' perceptions about environmental comfort inside an aircraft cabin, through probabilistic neural networks and general regression neural networks. The two alternative models are constructed using the physical environmental parameters as input–output patterns, reproducing real flight conditions (inputs) and the environmental comfort index (output), resulting from statistical analysis of passengers' judgments during test campaigns. The values for the spread parameters characterizing the Gaussian neuron activation functions in the two models are chosen in order to perform the better generalization of new data in the cases of discrete and continuous data, respectively. Results show tight correlation between estimated and actual comfort in both cases. The constructed networks being able to model human judgments about aircraft comfort starting from environmental parameters represents good tools for near-future aircraft design.

I. Introduction

NOWADAYS, evaluation of passengers' and crew's comfort inside the cabin is of key importance for modern aircraft designers; this task is not straightforward as it may seem at first sight, because human perception of comfort is subjective and depends not only on environmental conditions such as temperature, humidity, noise level, vibration, pollutants, and so on, but also, and for a not negligible part, on personal conditions such as health, physiology, and psychological attitude. In general, the definition of comfort is itself odd, because what is actually perceived is the discomfort and it can only be evaluated by the person himself. Modeling the passenger's evaluation of comfort through a mathematical tool is essential for obtaining a software tool to be used by aircraft designers to optimize, together with the aircraft performances, the perceived comfort. Approaches for modeling passengers' judgments about comfort should take into account both environmental and personal conditions and also the highly nonlinear nature of the human judgment process.

The aim of the reported investigation is to design a mathematical model reproducing results of human judgments about environmental comfort inside aircraft cabins and its implementation by means of a computational tool based on artificial neural networks (ANNs) to be then used to reckon comfort levels for new possible environmental conditions under study.

In the 1980s, following the exploit of the new regional turboprop aircraft, when internal noise comfort in aircraft was consistently addressed for the first time after a long period in which few general works could be found [1], the attention of designers was primarily addressed to vibration as a source of noise. The high internal noise levels were supposed to be essentially an effect of the propellers that, exciting the vibrations of the main structure, radiate inside the cabins. On these assumptions, several control systems, both active and passive, were developed in order to reduce vibration levels and hence improve the comfort. Soon, however, the vibration and noise fields were discovered to be not strictly related to each other, in the sense that controlling the vibrations was not always a guarantee of noise attenuation [2]. This was essentially due to the different capabilities of radiating noise by vibrations at different frequencies.

The focus of the scientists was translated to noise reduction by considering noise parameters, and results were obtained in the automotive field for interior car noise reduction [3]: to increase the comfort in noisy interiors, it is necessary to consider the subjective response of passengers.

The metrics related to comfort are not unique; a lot of psychoacoustic parameters [4] can be dealt with if the subjective response is desired to be taken into account: for instance, loudness, which can be associated somehow with low-band-frequency content; sharpness, which can be associated instead with high-band-frequency content; tonality, which takes into account the presence of response peaks in narrow bands; fluctuation strength, which considers variations of the spectral response during the time; roughness, which considers instead the pure broadband characteristics; and so on. The five mentioned parameters are, however, the most recurrent in the classical description [4]. The psychoacoustic parameters are estimated from both objective and subjective perspectives: estimations are usually made through elaboration of the physical output (acoustic response, hence objective) and elaboration of human answers (hence subjective). The two responses are correlated, but it is difficult to extract a unique and direct appreciation of the comfort impression.

Another relevant problem is concerned with the necessity of performing very large experimental campaigns for collecting a limited amount of data: a huge number of people have to be involved in order to acquire just sufficient reference data that must be statistically analyzed; the response of people has to be extracted from dedicated questionnaires based on semantic differences and elaborated by psychologists.

At the end of the process, the overall result is not so easy to be tracked in an absolute answer referring to a scalar metric: Is the environment perceived to be comfortable (and to what extent)?

On these bases, the European Union funded a certain number of projects substantially directed at improving the knowledge of the psychological aspect of comfort. With particular reference to the aeronautic field, IDEA PACI (Identification of an Aircraft Passenger Comfort Index) [5] had the double aim at developing a synthetic scalar index to evaluate the vibroacoustic comfort level and elaborate a specific mathematical tool to simulate and predict the human response to a typical vibroacoustic environment. The first goal was evidently targeted to synthetically express the quality of a cabin [6]; the second goal was to release a design tool, the so-called Virtual Passenger, that could simulate the subjective point of view of passengers inside a cabin. The Virtual Passenger was developed by means of artificial neural networks that were introduced for simulating passenger answers about vibroacoustic aircraft comfort, and the attained results seemed very interesting and promising for modeling comfort evaluations (depending not only on vibroacoustic parameters such as spectrum, energy content, noise levels, etc., but

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*Researcher, Vibration and Acoustics Laboratory; a.brindisi@cira.it.
†Researcher, Vibration and Acoustics Laboratory; a.concilio@cira.it.

also on other environmental conditions) and to facilitate the setup of further research.

One of these continuation programs [namely, HEACE (Health Effects in Aircraft Cabin Environment)] [7] had the aim of considering the physiological effects on the response and themselves as a consequence to the acoustic environment. Another point that was addressed consisted of considering the effects of the noise field on the crew work environment, investigating other important aspects such as the attention capability, the physiological stress value, and so on. The study extended the parameters of interest to temperature and air quality, wanting to assess the effect of change in one parameter on the overall comfort and health. ANN-based design tools were further exploited in this case [7].

Artificial neural networks are computational tools to solve different kinds of problems in a wide range of application fields. They have been successfully tested in many applications in the aeronautics field (for example, controllers [8], structural dynamics simulators [9], or generic predictors of unknown experimental measures or physical coefficients [10]) with satisfying results. In particular, they have been used as simulation tools to reproduce the generic human response to vibration and acoustic excitations with very promising attainments [11]. Recent studies aim at applying adaptive nets: that is, systems able to learn online, during the operational life, to control noise [12].

The work herein presented was developed for the European cooperation research program FACE (Friendly Aircraft Cabin Environment). New aspects developed for the present work concern a model of comfort judgments related to a refined and synthetic characterization of the aircraft cabin interior: environment is characterized by temperature, relative humidity, and noise levels. The comfort judgment is expressed by a scalar index [namely, the environmental comfort index (ECI)], synthetically representing the subjective comfort perceived by passengers sitting in a mockup during flight simulations; it was obtained by statistical estimations of their answers to a dedicated questionnaire based on semantic differences regarding personal wellness and perceived comfort and elaborated following psychological considerations. The methodology for obtaining the ECI was developed and applied by the partners of the project.

Two distinct approaches were proposed for the modeling: classification and functional regression, implemented through two different ANNs models: the probabilistic neural network (PNN) and the general regression neural network (GRNN), respectively.

The two networks are similar and present common characteristics in behavior and structure; both perform estimation of the parent probability density function by using neuron activation functions of Gaussian form. These functions are characterized by a free parameter, the variance, which can be set opportunely according to performance considerations: distinct values would lead the network to be more or less sensitive to data.

The main difference, and what for us is another interesting property, is that they are somewhat complementary; in fact, the former is a classifier, in the sense that it labels inputs according to a discrete scale, whereas the latter performs functional regression of continuous variables.

In the next sections, it is reported how the PNN and GRNN models are constructed as well as the respective evaluated performances. A critical review and the assessment of the presented results conclude the work.

II. Problem at Hand

The problem at hand can be seen as a system estimation problem in which the domains of input and output are given and the unknown system S connecting the two should be determined (Fig. 1) [13]. The available data set is composed of a limited number n of input–output patterns $\{\underline{X}_n, Y_n\}$, where every input vector $\underline{X}$ is three-dimensional and composed of measurements of physical parameters, and Y is the corresponding estimation of the output and it is a scalar.

Physical parameters characterizing the cabin interior are temperature, relative humidity, and noise level, which can be seen as stimuli for passengers, and their judgment about comfort is synthesized in the environmental comfort index.

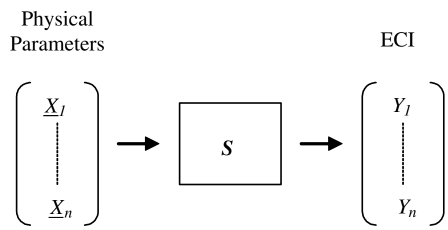

Fig. 1 System S connecting the physical parameters to the ECI has to be determined.

Data present a certain dispersion: subjective judgments about comfort regarding environment as a whole are more dispersed than judgments about comfort regarding a single parameter such as noise level. That is, if the comfort impression is related to a single parameter, passengers substantially agree about comfort judgments; instead, if comfort impression is related to a set of different parameters, passengers provide a wider range of judgments about comfort. The modeling of human judgments about environmental comfort should take into account this intrinsic dispersion.

The values of the ECI are a result of statistical elaborations; hence, values are real and the system S can be seen as generating either discretized (considering the original subdivision of the possible answers of questionnaire) or continuous values. In the former case, the system estimation problem can be seen as a classification problem [14] in which input data representing environmental conditions inside an aircraft should be classified (i.e., labeled) as more or less comfortable according to a discrete scale. In the latter case, the system estimation can be viewed from another perspective: it can be performed by a regression of the function mapping the input space to the output space. Parametric regression needs an a priori knowledge of the functional form, usually polynomial, and a best fit must be accomplished to estimate unknown parameters such as the coefficients of the polynomial [13]. For the problem at hand, an a priori knowledge of the functional form is not available, and nonparametric and highly nonlinear regression must be performed because we have to implement human judgments.

III. Probabilistic Neural Network and General Regression Neural Network

"A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use" [15]. Knowledge is acquired by the network through a learning process. Interneuron connection strengths, known as synaptic weights, are used to store knowledge. Artificial neural networks are composed of a number of computing units, called neurons, disposed in layers and fully connected in the sense that every unit in each layer of the network is connected to every other unit in the adjacent forward layer. Topology of networks sets the number of neurons, layers, and connections. A set of inputs vectors is multiplied by a set of weighting coefficients; the results constitute the arguments of functions (namely, the neuron activation functions) that produce the output in order to feed the following layer or to directly produce estimation of the output of the network. The weighting coefficients are calculated during the training phase of the network through a training algorithm by using sample data [14–16]. There are several kinds of artificial neural networks characterized by different topologies, training algorithms, and processes; one kind of network can reach optimal performances on a particular set of data and very poor performances on a different set. The choice of the appropriate network depends on the data characteristics, size, compositions, dispersions, and so on [17].

The dispersion of data suggested that the use of artificial neural networks, such as the probabilistic neural networks [18,19] and general regression neural networks [20], could be tailored on data and could hence present a behavior less sensitive to the noise of data by tuning a free parameter.

A. Probabilistic Neural Network

Probabilistic neural networks are widely used in the area of pattern recognition, nonlinear mapping, associative memory, and classification. PNNs perform classification by estimating the probability density functions (or pdfs) for various classes as learned from training samples that provide the only clue to the unknown quantities. They use the pdfs to compute the nonlinear decision boundaries between classes in a way that approaches the Bayes optimal [18]. PNNs implement the Parzen window estimator [21] by using a mixture of kernel basis functions and can be generalized to multidimensional functions, as shown by Cacoullos [22].

By using Gaussian functions as a kernel, the probability density function $f_Y(\underline{X})$ for a given category Y can be estimated by the following equation [20]:

$$f_Y(\underline{X}) = \frac{1}{(2\pi)^{p/2}\sigma_{\mathrm{PNN}}^p}\frac{1}{n}\sum_{i=1}^{n}\exp\left[-\frac{(\underline{X}-\underline{X}_{Y,i})^T(\underline{X}-\underline{X}_{Y,i})}{2\sigma_{\mathrm{PNN}}^2}\right] \quad (1)$$

where $\underline{X} = [X_1, \ldots, X_p]$ is the p-dimensional test vector of input measurements, $\underline{X}_{Y,i}$ is the ith training vector labeled with category Y, i is the pattern number, n is the total number of input–output training patterns, and σ_{PNN} is the variance. The estimated pdf is expressed as a sum of n multivariate Gaussian distributions centered at each training input. However, the sum is not limited to being Gaussian; it can approximate any smooth density function. The parameter σ_{PNN} defines the width of the Gaussian functions of the PNN and acts as a smoothing parameter and softens the surface defined by the multiple Gaussian functions.

The PNN classifier decides which class the test vector (or new data) belongs to, as the class having the maximum probability of being correct, depending on the degree of similarity of the input test vector to the model of each class.

Training consists of straightforwardly implementing Eq. (1): it is a one-pass process and does not involve iterations. Topology is simply determined by the number of input–output training patterns and classes: it constitutes two layers of neurons, as shown in Fig. 2. The first layer is the *pattern layer* composed of a number of neurons (*pattern neurons*) equal to the number of input training vectors, and the second one is the *competitive layer* composed of a number of neurons equal to the number of classes. The output neurons compete among themselves for being the one to be active: a single output neuron is active at any one time. In this way, the network discovers the statistically salient feature used to classify input vectors.

The weight vector $\underline{W}_i$ of the first layer is set equal to the input training vector $\underline{W}_i = \underline{X}_i$; this directly reproduces the fact that activation functions are centered in each training input point. Hence, training consists of essentially directly constructing the network by using the training set, which is, in a way, hardwired in the network.

The test input vectors feed the first layer characterized by activation functions of Gaussian form. The pattern neurons form a dot product $Z_i = \underline{X} \cdot \underline{W}_i$ of the input test vectors $\underline{X}$ with weight vectors $\underline{W}_i$ and compute the nonlinear operation expressed in the exponential of Eq. (1). Each Gaussian has the Euclidean distance between a test input and the training input as an argument. It acts as a proximity sensor: it gives a measure of how close a test input is to a training input and how close the output of the corresponding Gaussian is to its maximum. The second layer makes a decision according to probabilities computed at the previous stage. Finally, the output provides the identification number of the class, among k classes, that has the maximum probability of being the correct one.

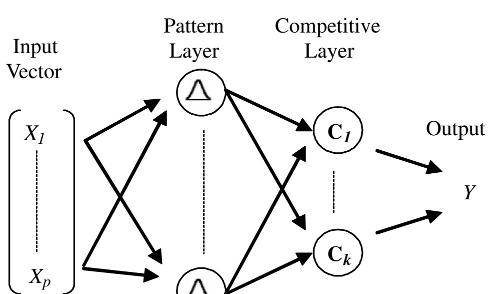

Fig. 2 Architecture of a probabilistic neural network.

B. General Regression Neural Network

GRNNs are proved to perform general regression providing estimates of continuous variables and converge to the underlying function by expressing the functional form as a probability density function empirically determined from the measurements of the data (i.e., from the input–output patterns [20]). The regression of the dependent scalar variable Y on the independent vector variable $\underline{X} = [X_1, \ldots, X_p]$ is determined as the estimation of the most probable value for Y, obtained from a limited number n of noisy measurements $\{\underline{X}_n, Y_n\}$ of the variables $\underline{X}$ and Y, respectively. This is done, as for the case of PNNs, using the Parzen window estimation [21]. The regression of Y on $\underline{X}$ [i.e., the estimated value for $Y(\underline{X})$] is expressed by the following equation [20]:

$$\hat{Y}(\underline{X}) = \frac{\sum_{i=1}^n Y_i \exp\left[-\frac{(\underline{X}-\underline{X}_i)^T(\underline{X}-\underline{X}_i)}{2\sigma_{\mathrm{GRNN}}^2}\right]}{\sum_{i=1}^n \exp\left[-\frac{(\underline{X}-\underline{X}_i)^T(\underline{X}-\underline{X}_i)}{2\sigma_{\mathrm{GRNN}}^2}\right]} \quad (2)$$

where n is the number of the given patterns, and σ_{GRNN} is the width of the estimating kernel. This equation can be seen as a weighted average of all the observed values Y_i. As σ_{GRNN} becomes very large, it assumes the value of the mean of the n measures Y_i; as σ_{GRNN} becomes small, it assumes the value of measure Y_i associated with the observation closest to $\underline{X}$.

Equation (2) can be implemented by a network having a structure similar to that of PNNs: general regression neural networks are, in a way, similar to the probabilistic neural networks, and considerations made for them in the previous section also hold for GRNNs.

As for the previous case, GRNNs are constituted by two neuron layers, with the first layer composed of a number of neurons equal to the number of input–output patterns and characterized by activation functions of Gaussian form. The two networks presented here differ for the second layer: for the GRNNs, the second layer is composed of a number of neurons equal to the number of input–output patterns and presents linear activation functions, for which the output is the output of the whole network.

In both presented networks, the Gaussian activation functions are characterized by their widths, or spread parameters, the σ_{PNN} and σ_{GRNN}, respectively, defining the region around a given input for which the neurons of the pattern layer would respond with significant output. Very small values of the spread parameter would lead the estimated pdf to show distinct modes corresponding to the locations of training samples [18–20]; the network is said to follow the training data too much; in this case, the network itself is said to be highly sensitive to the data. On the other hand, very large values of the spread parameter would lead the Gaussians to overlap significantly, which would cause the estimated pdf to have a Gaussian form regardless of the true underlying distribution [18–20], the network to always restitute the same output value determined by the mean of the possible outputs, and the network to be insensitive to single variations of data; in this case, it is said to be too robust.

The σ_{PNN} and σ_{GRNN} are free parameters, and suitable values for them must be selected according to considerations on network performances.

IV. Implementation of the Networks

In this section, the details of the implementation of the networks in the two cases are shown. The first step is the settlement of the topology of each network and the preprocessing of data by means of their normalization. The input domain for the function to be estimated represents the physical conditions of the environment inside the aircraft cabin, and the output domain gives a measure of the comfort perceived by the passenger seating in the cabin. The former is three-dimensional and composed of temperature (°C), relative humidity (%), and noise-vibration level (dB). The latter, representing the environmental comfort index, is a real scalar value. The given data set is composed of a number $n \sim 1000$ of input–output patterns.

The inputs are three-dimensional vectors of variables of different natures and with different ranges of variability. To have a kernel with the same width in each dimension for the probability density function, the numerical data have been homogenized and a normalization has been performed: each input variable has been mapped into the range of −1 to 1. The maximum distance between two points in the three-dimensional input space of size 2 in each dimension has been calculated using the Euclidean distance and resulted in being about 3.5. Thus, for both cases, the spread parameters characterizing the transfer functions of the neurons can be varied in the range of 0–3.5.

As said before, the ECI has been obtained by statistical estimations of the passengers' answers of a dedicated questionnaire based on semantic differences; hence, considering the original subdivision of possible answers, their values are real and can be discretized. According to cognitive aspects, as Miller [23] stated, there is a limitation on the span of human absolute judgment, as for the case of semantic differences: if asked how good or bad a certain thing is, a human is able to discern, at most, a scale of 7 values, plus or minus 2. This results in severe limitations on the amount of information that humans are able to receive and process. According to this, the evaluations performed by passengers about comfort and personal wellness were based on absolute judgments on a scale of 7 values. Following these considerations, a discretization of the output (comfort) values in 7 classes was performed for the case of classification to be performed by the PNN model.

To avoid uneven distribution of instances in classes (some classes may contain many items and some others may contain none), an equal-interval binning [17] has been chosen. This kind of binning allows different classes with different sizes but the same number of instances: every class is equally represented.

The PNN to be constructed for classifying human perception of aircraft environmental comfort presents a topology in which the pattern layer has the number of neurons equal to the number of input patterns ($n \approx 1000$) and a competitive layer with the number of neurons equal to the number of classes ($k = 7$).

The GRNN to be constructed for modeling the passengers' judgments presents a topology in which the pattern layer and the linear layer each have a number of neurons equal to the number of input patterns ($n \approx 1000$).

IV. Performance Estimations

Assessments on network performances are important to understand how good our model is at capturing the behavior of the unknown system S (Fig. 1) and, at the same time, to predict comfort for new values of environment (i.e., to classify new environmental conditions or to perform generalization in the continuous-variable case). Performance assessments can be done by estimating the errors committed by the networks on training and on new data, respectively. The training error, or resubstitution error, is obtained by resubstituting the training inputs into the network that was constructed from them. The training error is not a reliable predictor of the true error on new data: it is too optimistic. A better estimator is the testing error obtained by feeding the network with new data not involved in the network construction [17]. This family of networks presents a degree of freedom; it is characterized by the variance σ, or spread, which is a free parameter to be set according to performance considerations. By minimizing the error on new data with respect to this free parameter, the network performs a better prediction of comfort among new possible environmental conditions.

In Fig. 3, theoretical [14,15], test-error, and training-error trends are plotted versus the spread parameter σ for a generic network presenting the activation function of Gaussian form. It can be seen from the figure that the training error decreases, and hence training performance increases, monotonically from bigger to smaller values

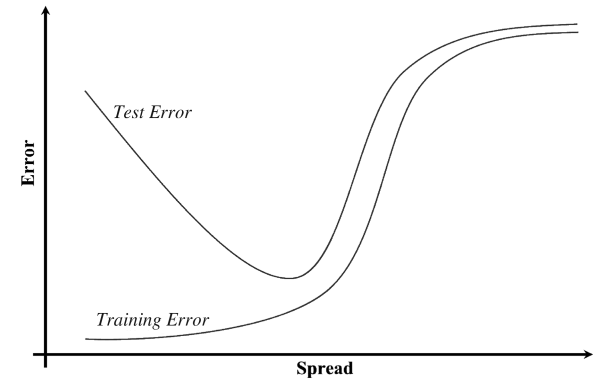

Fig. 3 Typical test-error and training-error trends vs spread σ for a generic network [14,15].

of σ, and the test error shows a clear minimum, corresponding to a certain value of σ.

This happens because, from this certain value of σ, the network under training becomes too specialized: it learns to well reproduce the training data, but loses generalization ability. In fact, for smaller values of the parameter, the training error decreases and the network well reproduces the behavior of the system S on these data; the network is said to show highly sensible behavior. In other words, for $\sigma \to 0$, the training error is minimized and overfitting occurs.

On the other hand, for bigger values of σ with respect to the minimum condition of the test error, the network has not learned enough and tends to give almost the same value, regardless of the variability of test input vectors: the network shows a too-robust behavior. Thus, the other limiting case, $\sigma \to \infty$, should be avoided as well; in fact, the true underlying distribution is, in this case, underfitted.

To perform a better prediction among new possible data, we should minimize the test error and pick the value of spread for which this condition is verified; in other words, we should accomplish a balance between network sensitivity and robustness, avoiding both overfitting and underfitting.

A. Performances Estimations for PNN

Evaluation of performance for a classifier can be made by considering the error rate, or misclassification ratio [17]; an input vector is said to be misclassified if it is classified as belonging to a class different from the correct one.

For the purposes of our research, the misclassification ratio is not exhaustive information. Because the classes are ordered descending from the discretization of real values, misclassifications occurring for uncontiguous classes represents a bigger cost. A misclassification of input data belonging, for example, to class 2 with class 4 has a bigger cost than a misclassification with class 3. Hence, we consider the cost matrix $\boldsymbol{M}$, for which the elements are expressed as $\boldsymbol{M}_{ij} = |i - j|$; according to this, the bigger the distance between the actual (or target) and predicted class, the bigger the cost. By weighting the misclassification ratio with the cost matrix $\boldsymbol{M}$, we obtain the estimation of the performance of the classifier as

$$\frac{1}{n}\sum_{n}|p_n - t_n|$$

where p_n and t_n represent, respectively, the predicted and target outputs. This expression is, by the way, the definition of the mean absolute error (mae) [17], defined as the average of the absolute errors.

To obtain a network that performs the better classification of a new environment condition and to set the value of the free spread parameter, two different test suites are accomplished: the first to evaluate the training error and the second to evaluate the test error.

Because the data at disposal are limited in number, the whole data set is used for the first test suite, and the holdout method [20], also called *leave-one-out* in some literature [17], is applied to the selection of the numerical value of the spread. This method generally consists of holding one pattern out, constructing the network with the remaining patterns, and evaluating the obtained network on the input left out. The difference between the target and predicted output is the error made by the network in predicting the comfort for that particular new environmental condition. This procedure enables us to obtain the maximum out of a small data set.

The evaluation of network performance on training data is straightforward; in the first test suite, the mean absolute error is calculated for the training data by varying the spread parameter in its range of variability. In Fig. 4, the mae is plotted vs the spread σ_{PNN} in the full range of 0–3.5 (left) and in zoomed range around $\sigma_{PNN} = 0.03$ (right). The training error decreases monotonically from bigger to smaller σ_{PNN} values, as expected from Fig. 3.

In the second test suite, the evaluation of the network performance on new data is made with the leave-one-out procedure. The test error should be calculated for each point belonging to the data set, and the consequent mean absolute error is an estimate of the performance of the network in classifying new data.

The value of σ_{PNN} corresponding to the smallest test error should be used in the final network. In Fig. 5, the mae corresponding to the new data is plotted in the full range of 0–3.5 (left) and in zoomed range around $\sigma_{PNN} = 0.03$ (right), and it reproduces the trend as expected from Fig. 3.

For σ_{PNN} ranging from ≈ 1 to large values, both the performances on training and new data are approximately constant and poor; in this range, the network does not learn and is not able to properly estimate the pdf: the network is too robust. For smaller numerical values of the spread, the performances of both types of data improve rapidly. In particular, for $\sigma_{PNN} = 0.03$, the mae calculated for the new data shows a clear minimum (Fig. 5, right), in which the network performs the better generalization of data. For smaller values of σ_{PNN}, the mae on training data decreases and overfitting occurs: the network is highly sensible.

For the value of the $\sigma_{PNN} = 0.03$, the performance in estimating the comfort on the training data is given by mae $= 0.035$ (Fig. 4), and the corresponding confusion matrix expressing the misclassifications is presented in Table 1. Good results correspond to large numbers along the main diagonal and small number along offdiagonal elements.

Table 1 Confusion matrix

		Actual classes						
		1	2	3	4	5	6	7
Predicted classes	1	121	3	1	3	1	0	4
	2	3	120	1	5	3	5	0
	3	2	3	120	2	4	1	2
	4	1	5	3	113	4	3	4
	5	3	3	4	4	118	3	1
	6	2	1	2	3	2	119	4
	7	3	0	4	5	3	4	126

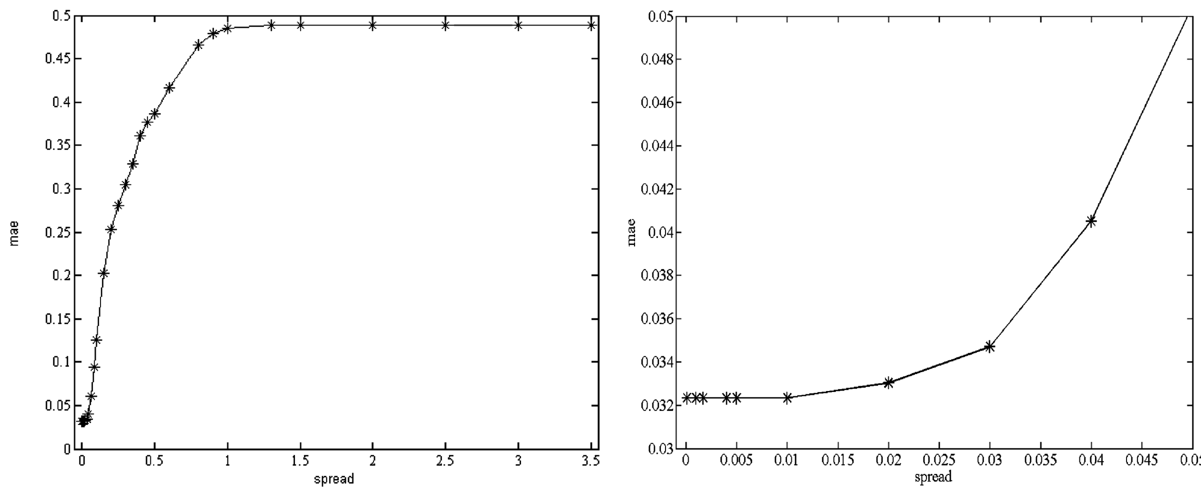

Fig. 4 Plots of mae vs σ_{PNN} in the full (left) and zoomed (right) range with training data.

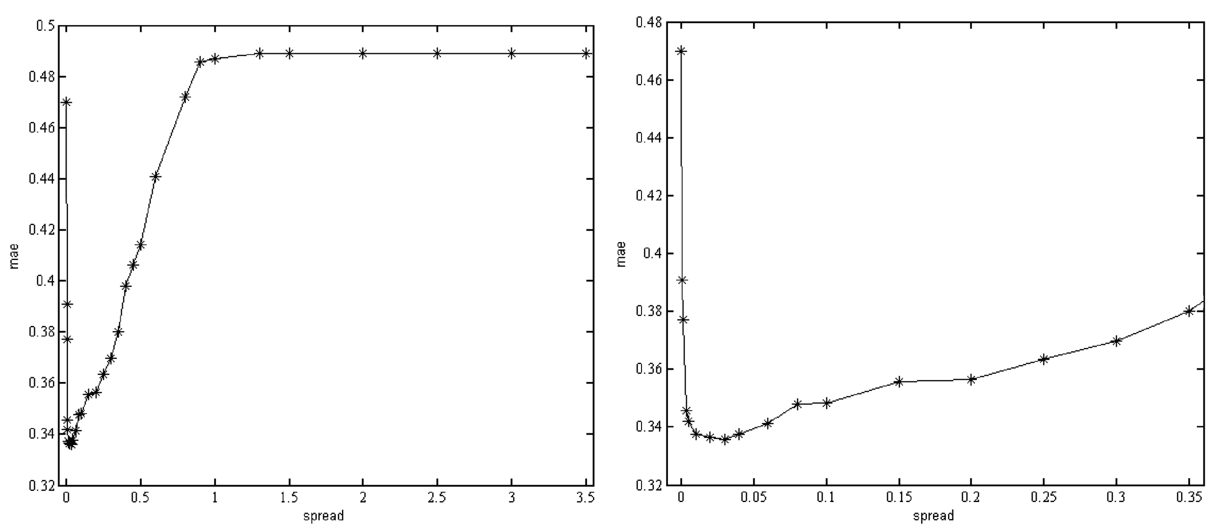

Fig. 5 Plots of mae vs σ_{PNN} in the full (left) and zoomed (right) range with new data.

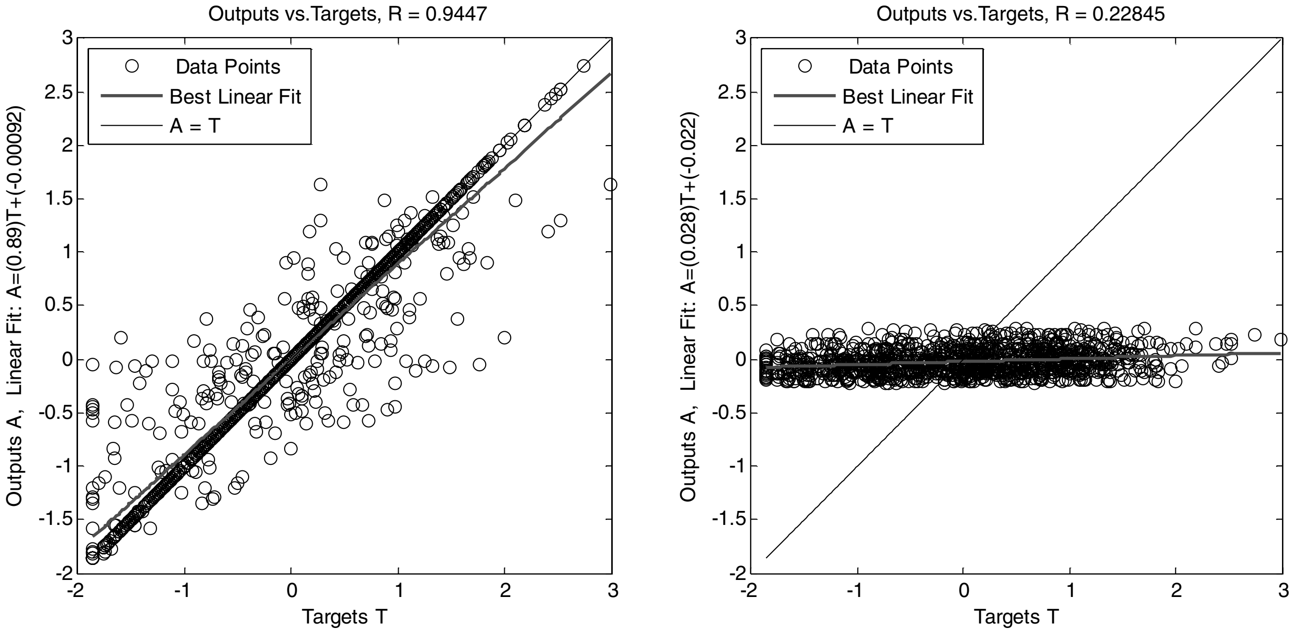

Fig. 6 Predicted comfort A vs targets T, $\sigma_{\mathrm{GRNN}} = 0.001$, and $R = 0.95$ (left) and $\sigma_{\mathrm{GRNN}} = 0.5$ and $R = 0.2$ (right).

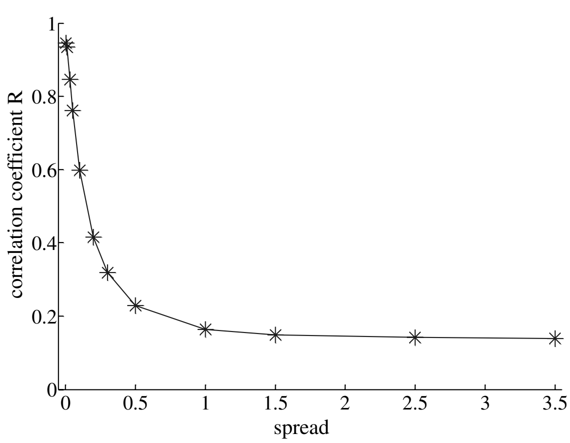

Fig. 7 Correlation coefficient vs spread parameter σ_{GRNN} with training data.

Therefore, the best choice for the value of the spread parameter is $\sigma_{\mathrm{PNN}} = 0.03$, for which the test error is minimized and, at the same time, a good performance on training data is evidenced, showing tight correlation between predicted and target data.

B. Performances Estimations for GRNN

For the continuous-variable case, approached with a GRNN, the evaluation of performance can be made by considering the statistical correlation between the predicted and target output variables [17]. Correlation can be computed by performing a linear regression between the two variables; the corresponding linear correlation coefficient R gives an estimation of the network performance. The correlation ranges from 1 for perfectly correlated results to 0 for totally uncorrelated variables. In Fig. 6, two plots of the predicted output variable vs the target variable are reported as examples, together with the corresponding linear fits, for two distinct values of the spread parameter $\sigma_{\mathrm{GRNN}} = 0.001$ (left), which produces well-correlated variables, and $\sigma_{\mathrm{GRNN}} = 0.5$ (right), which produces uncorrelated variables.

As for the previous case, 2 test suites are performed. In the first test suite, the performance of the network on the training data is evaluated as the spread parameter σ_{GRNN} is varied. It can be shown by plotting the R coefficient versus the σ_{GRNN} that the network performance on

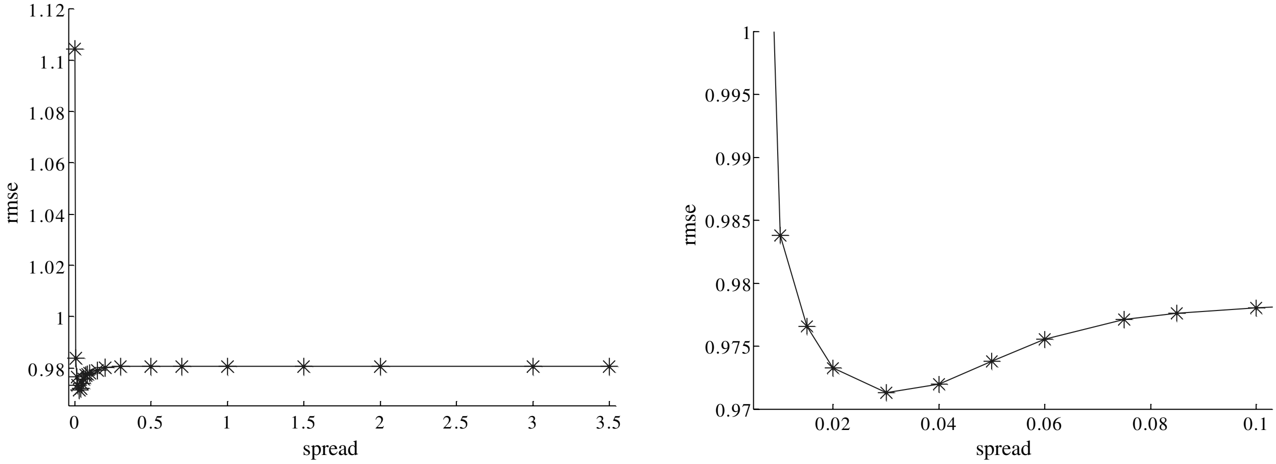

Fig. 8 Plots of rmse vs σ_{GRNN} in the full (left) and in a zoomed (right) range with new data.

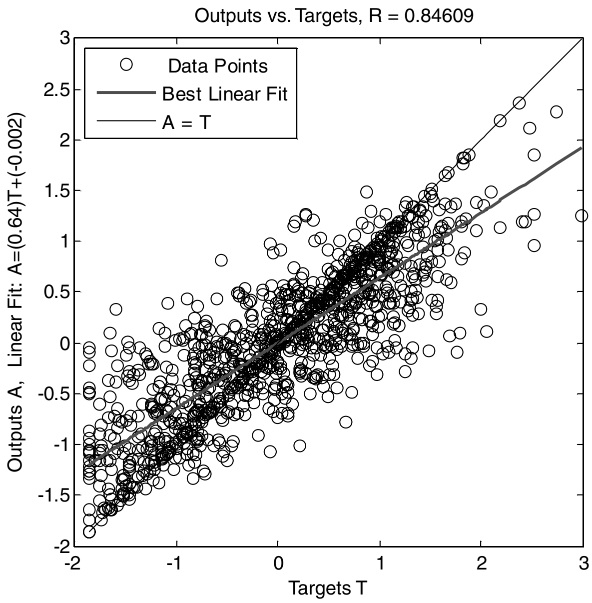

Fig. 9 Predicted comfort A vs targets T, $\sigma_{\mathrm{GRNN}} = 0.03$, and $R = 0.85$.

the training data increases while varying from large to small values (see Fig. 7).

In the second test suite, the evaluation of the network performance on new data is made with the leave-one-out method. The test error should be calculated for each point belonging to the data set, and the consequent root-mean-squared error (rmse) is an estimate of the performance of the network in classifying new data.

The value of σ_{GRNN} corresponding to the smallest error should be used in the final network. In Fig. 8, the rmse corresponding to the new data is plotted in the full range (left) and in zoomed range around $\sigma_{\mathrm{GRNN}} = 0.03$ (right).

Concerning the performance evaluations, the GRNN shows a behavior similar to the PNN. In fact, both performances, R on training data and rmse on new data, are poor and approximately constant for values of σ_{GRNN} starting from ≈ 0.5. As shown in Fig. 6 (right), for large values of σ_{GRNN}, the network is too robust and gives almost the same output, as expected from Eq. (2) and from Fig. 3.

For $\sigma_{\mathrm{GRNN}} = 0.03$, the rmse shows a clear minimum (Fig. 8); at this point, the network performs the better generalization of data. For smaller values of σ_{GRNN}, the performance on training data increases (Fig. 7) and overfitting occurs.

For the value of $\sigma_{\mathrm{GRNN}} = 0.03$, the performance in estimating the comfort on the training data is $R = 0.85$. In Fig. 9, the actual and predicted comfort on training data are plotted together with the best linear fit.

Therefore, as for the PNN case shown before, the best choice for the value of the spread parameter is clearly $\sigma_{\mathrm{GRNN}} = 0.03$, for which the better generalization is obtained and performance on training data is very good, showing tight correlation between simulated and target data.

V. Conclusions

In the present work, the approach based on use of an ANN-type algorithm is applied for the problem of modeling passengers' perceptions of aircraft cabin comfort regarding a characterization of an environment considering temperature, relative humidity, and noise level. Two different approaches are proposed for the modeling, classification, and functional regression, and two distinct models are developed: the probabilistic neural network and the general regression neural network.

The two developed models are complementary: the former can be used with discrete data and performs classification of environmental conditions, the latter, can instead be used with continuous comfort variables and provides comfort output by performing functional regression. The construction of the models is attained by searching for a balance between two possible distinct network behaviors, sensitivity and robustness (i.e., by setting the values for the free parameter σ in order to obtain the better performances on new possible data). This is done through the leave-one-out method.

The use of an activation function of Gaussian form enables adequately modeling the dispersion of data, which are due to a more refined characterization of the environment, through the setting of the free parameter σ.

The two presented models show good performances with tight correlation between the predicted and actual comfort values (Table 1 and Fig. 9); moreover, both reach the better performance on new data for the same value of the related spread parameter (Figs. 5 and 8), thus proving that they are, in a way, similar and complementary and, at the same time, confirming their goodness. The two models are useful tools to predict aircraft interior comfort values for possible environmental conditions under study. The choice of which, between the two proposed methods, should be used for future applications should be driven by the type and the amount of data at disposal and by the intended use of the model itself.

The proposed model could be easily embedded in a more general aircraft design software tool and provide comfort information in addition to other standard aircraft parameters.

Future research can be addressed toward a better characterization of the aircraft interior, including more parameters such as pressure gradients, pollutants, multimedia, and so on. Moreover, a network refinement can be accomplished by using different σ for different-pattern neurons.

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