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Application of a Neuro-Fuzzy System for Welders' Indisposition Forecasting

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Abstract In this study two data-driven models to forecast the indisposition of professional welders are presented and discussed. One is based on the Takaki-Sugeno adaptive neuro-fuzzy inference system (ANFIS), while the other is based on neural networks (NN). Both are parameterized with reference to the overall indisposition of welders. The analysis of the two models is performed using the same input and output variables. The analysis was made with great attention to the reliability, capability and accuracy of each model, with reference to a public shipyard company in Greece. It was shown that the ANFIS model based on the fuzzy logic approach performed better than the neural networks model.

Keywords ANFIS forecasting, overall indisposition, risk of welders, toxic gases concentration, ultraviolet radiation

1. Introduction

Welders in any industry are engaged in welding works approximately eight hours per day and exposed to many types of health problems. They can be prone to inhaling, ingesting, and coming into skin contact with welding fumes. All types of exposures contribute to disease outcome Gonser and Hogan, [5].

Welding workers' exposures are usually measured in the breathing space. There are two harmful factors resulting from electric welding which affect a worker during his shift. Vapors are released during the welding process, resulting in toxic matter that has the form of gases or solid body particles. The use of the electrical arc in the welding process produces a huge emission spectrum of ultraviolet radiation. Real data for toxic gas concentration and ultraviolet radiation are important to design an effective model to forecast the welders' indisposition.

There are various studies that forecast other types of fumes or other types of radiation produced. Yea et al. [19] estimated the inflammable concentration. Sterjovski et al. [18] developed and validated a back-propagation artificial neural network, to predict the level of diffusible hydrogen.

Despite a large number of publications on the pathophysiological processes of welding fume exposure, relatively few attempts have been made to determine the indisposition levels affected by welding fume exposure to identify early effect signs resulting from mixed exposure.

This study contributes to the existing literature in several ways. First of all, forecasting welders' indisposition has always been an important topic, but the hybrid research of evolutionary computation and statistical model is little. This is the first time fuzzy with neural networks are combined to form a neuro-fuzzy model to forecast the total indisposition of welders. Secondly, for the first time a neural network is applied to compare the performance of the models. Finally, this is first time that these data have been used to build the models.

The structure of the study is arranged in the following order: Section 2 presents the related research. Section 3 describes the theoretical background of the model. Section 4 presents the applied models. Model evaluation was carried out in Section 5 where an out-of-sample forecasting procedure was conducted. Finally Section 6 concludes the paper.

2. Related Research

Yea et al. [20] have proposed a method of estimating the concentration of inflammable gases from transient response patterns, using a semi-conductor gas sensor. The procedure took place for five selected gases: butane, town gas, and hydrogen, methane, and propane gas. The experiment proved that the discrimination of the five gases supported by a three-layered back-propagation neural network as well as the estimation of their concentration inference was successfully performed, due to the assistance of the fuzzy neural network.

Imamoglu *et al*. [9] carried out research to study the erythrocyte antioxidant system. The study took place among workers who were continuously exposed to welding fumes and gases, which are thought to be oxidant pollutants. The collaborated effects of smoking and other risk factors such as gases and welding fumes, which had been shown previously by some clinical data, should also be taken into consideration. As a consequence, the welders were warned and informed about the harmful effects of inhaling welding fumes and gases.

There are many reports about welders who have suffered from metal fume fever, lung function changes, bronchitis, as well as an increase in the incidence of lung infections. Antonini et al. [2] and Antonini et al. [1] carried out an experiment in order to examine the remaining questions about the mechanisms associated with the potential pulmonary effects of welding fume exposure.

Jeong et al. [12] investigated the effects of welding fumes on the histological structure and properties of mucins of the nasal respiratory mucosa.

Zimmera et al. [25] carried out a study in order to specify the effect from shield gas composition, droplet mass transfer mode and welding spatter on the aerosols that are derived from gas metal arc welding operations.

Further studies on the sequences of the radiation have been made by the scientific community. Mellit et al. [14] used an adaptive neuro-fuzzy inference system (ANFIS), which focused on estimating the sequences of the monthly mean clearness index and the total solar radiation data in isolated grounds, using geographical coordinates. Moreover, a multi-layer perceptron (MLP) has been used. Basically, longitude, altitude and latitude comprise the inputs of the ANFIS model, while the outputs are the 12 values of the monthly mean clearness index. As a result of that experiment as well as taking into serious consideration its mean values, an estimation of the root mean square error (RMSE) between measured and estimated values and the mean absolute percentage error (MAPE) took place. The first variable ranged between 0.0215 to 0.0235, while the second was less than 2.2%. Additionally, it was unavoidable to compare the results obtained by the ANFIS model and those from the artificial neural network (ANN) models, so as to present the advantage of the proposed method.

Mubiru [16] developed an artificial neural networks model, which could be used for predicting the daily total or monthly average solar radiation on a horizontal surface for various different locations in Uganda based on geographical and meteorological data, such as: sunshine duration, latitude, relative humidity, longitude, maximum temperature and altitude.

According to Oyabu [17], there are many different sensors and systems that have seen the light in order to detect disasters in domestic circumstances, like fires and gas leaks. The system adopts fuzzy reasoning, which is made up of simple membership functions and is capable of estimating the grade of each disaster.

For the purpose of the study, an ANFIS model was used for the first time as a tool of modelling and forecasting the indisposition which professionals involved in electric welding face. The model predicts the reaction of the workers’ immunizing system in terms of the total indisposition, against the fumes and the radiation of the welding run, after being exposed to it for a certain period of time.

3. Theoretical Background

3.1. Neuro-fuzzy approach

Fuzzy logic theory was first formulated by Zadeh [22 & 23] as a new way of characterizing non-probabilistic uncertainties. In contrast to the Boolean 1-0 logic, fuzzy logic also permits in-between values for any judged statement, i.e., it applies a continuous, multi-valued logic between 0 and 1. A fuzzy inference system (FIS) is a computing framework that combines the concepts of fuzzy logic, fuzzy decision rules, and fuzzy reasoning as

Jang [11] has highlighted.The fuzzy decision rules are the way a fuzzy inference system (FIS) relates an input variable χ to an output variable y. In the case where more than one variable is involved on the premise side, the structure of the rule takes the form:

If x_1 is A and x_2 is B, then y is Z (1)

where x_1 and x_2 are the input variables and *A, B*and Zare linguistic values (small or big etc.) defined as the membership function (MF) in the input and output spaces. The steps to create a fuzzy inference model are as follows:

Fuzzification: the input variables are compared with the MFs on the premise part of the fuzzy rules to obtain the probability of each linguistic label.

Calculation (through logic operators) of the probability on the premise part to get the weight (fire strength) of each rule.

Application of firing strength to the premise MFs of each rule to generate the qualified consequent of each rule depending on its weight.

Defuzzification: the qualified consequents are aggregated to produce a crisp output.

In early examples of fuzzy modeling, attempts were made to extract the fuzzy rules directly from the expert's knowledge. Later, new methods were developed which used an automatic process to generate the fuzzy rules, while taking advantage of neural network algorithms.

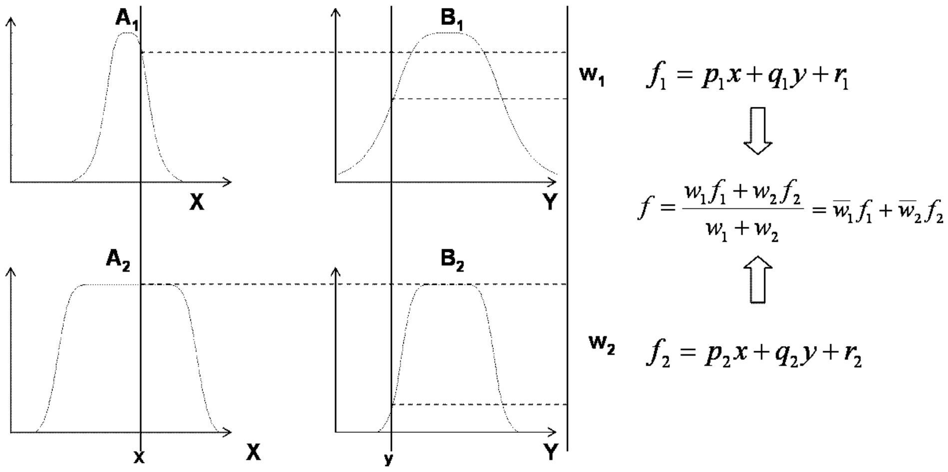

Figure 1: A two-input first-order Sugeno fuzzy model with two rules, Jang et al., [11]

A neuro-fuzzy system is defined as a combination of neural networks and the Fuzzy Inference System. Thus, Jang and Sun15 introduced an Adaptive Neuro-Fuzzy Inference System (ANFIS) where the MF parameters were fitted to a dataset through a hybrid-learning algorithm. The basis of the ANFIS model is the theory of artificial neural networks (ANN). Figure 1 depicts the fuzzy reasoning process of a first-order Sugeno-type fuzzy inference system (FIS), with two input variables (x and y), one output (z), and two if-then rules. Each input space has been characterized by two intuitively labeled membership functions (MFs), drawn separately for clarity, and the graphical representation of each rule. Figure 2 depicts the structure architecture of ANFIS.

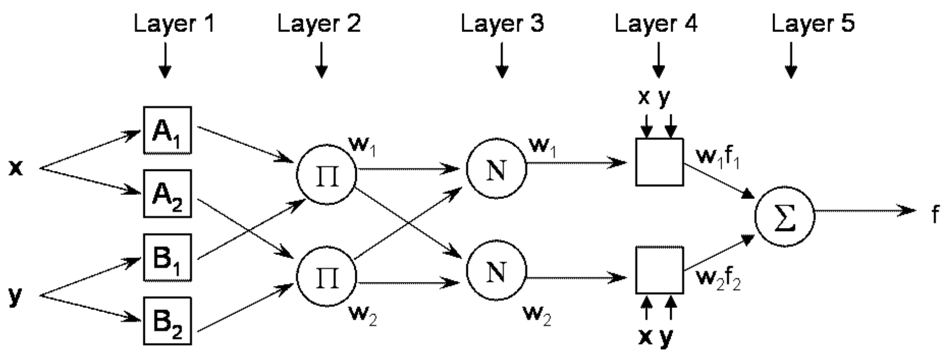

Figure 2: An illustration of the ANFIS architecture [11]

For simplicity, it was assumed that the examined fuzzy inference system has two inputs, x and y, and one output. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if–then rules is defined as:

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$ (2)

Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$ (3)

As seen from Figure 2, different layers of ANFIS have different nodes. Each node in a layer is either fixed or adaptive. Different layers with their associated nodes are described below:

Layer 1: Every node i in this layer is a square node with a node function.

$$O_{1,i} = \mu_{A_i}(x) \tag{4}$$

where x is the input to node i and A_i is the linguistic label (small, large, etc.) associated with this node. In other words, $O_{1,i}$ is the membership function of a fuzzy set A_i which specifies the degree to which the given input x satisfies the quantifier A_i .In this study $\mu_{A_i}(x)$ of a triangular shape was used with a maximum value equal to 1 and a minimum value equal to 0:

$$trimf(x,a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{5}$$

where a_i, b_i, c_i is the parameter set. As the values of these parameters change, the triangular-shaped functions vary accordingly, thus exhibiting various forms of membership functions for fuzzy set A_i . Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labelled ∏, which multiplies the incoming signal and sends the product out:

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \ \ i = 1, 2. \tag{6}$$

Layer 3: Every node in this layer is a circle-fixed node labelled N. The i-th node calculates the ratio of the i-th rule’s firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,\ 2. \tag{7}$$

For convenience, the outputs of this layer are called normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive square node with a node function

$$O_{4,i} = \overline{w}_i \cdot f_i = \overline{w}_i (p_1 \cdot x + q_i \cdot y + r_i) \tag{8}$$

Where $\overline{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set in this layer. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a circle-fixed node labelled ∑, which computes the overall output as the summation of all incoming signals:

$$overall\ output = O_{5,i} = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \tag{9}$$

As Jung [11] has presented, this architecture develops an adaptive network that is functionally equivalent to a two-input first-order Sugeno fuzzy model with four rules, where each input has two membership functions. The main advantage of this model is its transparency and efficiency. The ANFIS model was implemented in a Matlab environment which is available in the Fuzzy logic Toolbox.

3.2. The Artificial Neural Network approach

Neural networks try to imitate the function of the brain and for this reason the connections between neurons determine the function of the network. They are constituted by highly interconnected simple elements called artificial neurons which receive information, elaborate it through mathematical functions and pass it on to other artificial neurons. In particular, in multilayer perceptron feed-forward networks, the artificial neurons are organized in layers: an input layer, one or more hidden layers and an output layer, Hagan et al [6]. In this study, one hidden layer is considered, since it is shown that this type of network can approximate any function, McNelis [13].

The full definition of an NN model implies the quantification of the number of neurons in the hidden layer and the weight values, since the neuron numbers in the input and output layers are fixed by the numbers of input and output variables, respectively.

Nevertheless, with regard to the neuron number in the hidden layer, it is usually defined by a trial and error procedure, searching for the lowest number of neurons without penalizing model efficiency (Hsu et al. [8]; Zealand et al. [24]; Chiang et al. [3]).

As regards the quantification of the weight values, two different algorithms are frequently used to train the model: the Levenberg Marquardt algorithm (Hagan and Menhaj [6]) and the scaled conjugate gradient algorithm (Moller, [15]). Hence, the former algorithm seems to perform better with ANN models characterized by few neurons, and thus few weights, while the latter with ANN models is characterized by many neurons, and thus many weights. In order to avoid over-fitting and to improve the ANN model robustness, an early stopping procedure was used (Demuth and Beale, [4]). In this procedure three data sets are considered: training, a validation and a testing set. The first and second subsets are used to setup the model, and a third subset to test it. More in detail, the first subset was used for training the model. At each training step, the calibrated model is validated using the second subset. While the first training steps are performed, the error decreases, as it does in the corresponding validation phase. As the model begins to overfeed the data, the error in the validation phase begins to rise and thus the training procedure is stopped. The artificial neural network model was implemented in the Matlab environment where it is available in the Neural Network Toolbox.

4. Method presentation

4.1. Inputs, output & data collection

The data used in this study refer to a public shipyard company of Greece. The presented experiment to model the risk that professionals of electric welding face started by recording the harmful factors caused by the electric welding which affects the worker during a shift, i.e. the vapors released during the electric welding as well as the ultraviolet radiation that is produced.

The workers spend half of their shift in the workshop and the rest of it on the ship. The place where the samples were gathered from referred to the boiler works, a big room with sufficient air flow (therefore, there was an existence of quick refreshment of air in the workplace) and, as a result, nobody could expect a large concentration of gases in the space from the welding, which was verified by the samples. Samples for a gas cloud were carried out with VOC, a machine from the Noetic Ergonomics and Security Lab., which calculates gas concentration in ppb. As long as the ultraviolet radiation was concerned, a machine was used, which calculates ultraviolet radiation in $\mu W/m^2$.

According to a presidential decree, a welding worker's shift lasts for 4 hours at most. So the samples were taken with a frequency of 2 minutes for 2 hours of continuous welding (which is half the shift). In this way, it was possible to gather 120 samples (120 moments) which were sufficient to successfully train the proposed system.

The collection of the samples was initially carried out with a visit to the workshop which, because of the good ventilation, is considered an open area. The ventilation of air was always over 1m/s* and the atmosphere was refreshed 4 times per hour, almost every 15 minutes, which is considerably good. In this part, it is possible to clearly distinguish the effect of the harmful factors of electric welding on the workers and the way they are affected.

Each worker was initially asked to inform us on the indisposition they felt every 2 minutes (time defined as the moment of the sample) using a 10-point scale, where 0 denoted that the worker was not affected at all from either the cloud of gases or the radiation, and 10 indicated that it was unbearable for him. The type of electrode that was chosen was the ordinary one which is often used, and so the procedure for taking samples began. The samples were taken at the height of the head of the worker, so that a correct and precise picture of what enters the respiratory system and the radiation that reaches him could be taken.

A remarkable observation that comes up from the board is that the ventilation of the room almost every 15 minutes causes a decrease of gas levels released with the same frequency. The data of the input variables of toxic gas concentration (ppb) and radiation ($\mu W/m^2$) and the output variable of total indisposition were fed to the ANFIS and NN models. Therefore, the models learn to forecast the total indisposition of the worker relating to the gas concentration in the room and the radiation. Figure 3 depicts a part of the collected data used to create and evaluate the proposed model.

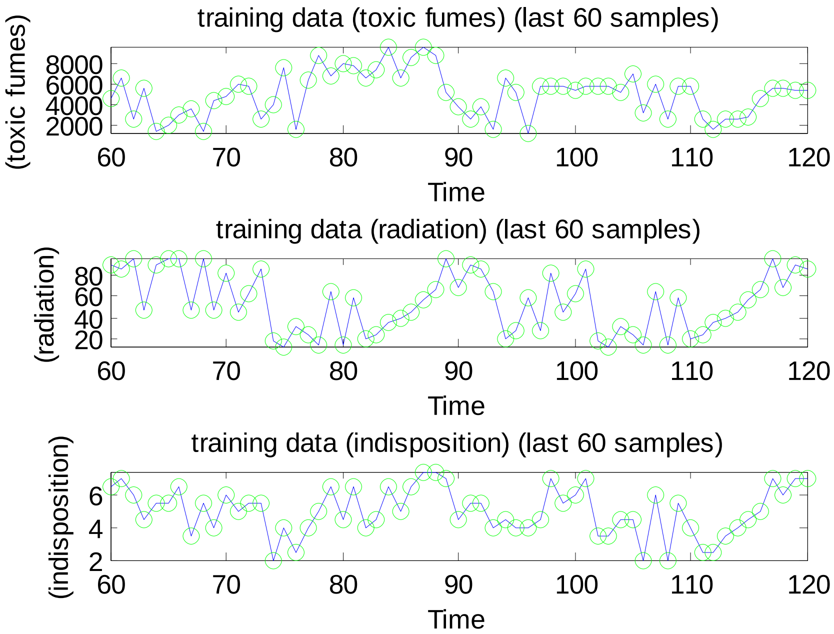

Figure 3: A part (60 samples) of the training and evaluation data

Figure 4 presents a scatter plot of the training data. As can be seen the data are not distributed across the input space of the model in a uniform manner. This is due to the type of data. The lack of data at the lower right corners of the input spaces enables the creation of a sharp ascent or descent at each of the surface corners of Figure 5. Figure 5 illustrates a three-dimensional surface of the neuro-fuzzy model. This is a smooth non-linear surface which states that the indisposition increases as the radiation and toxic fumes are increased.

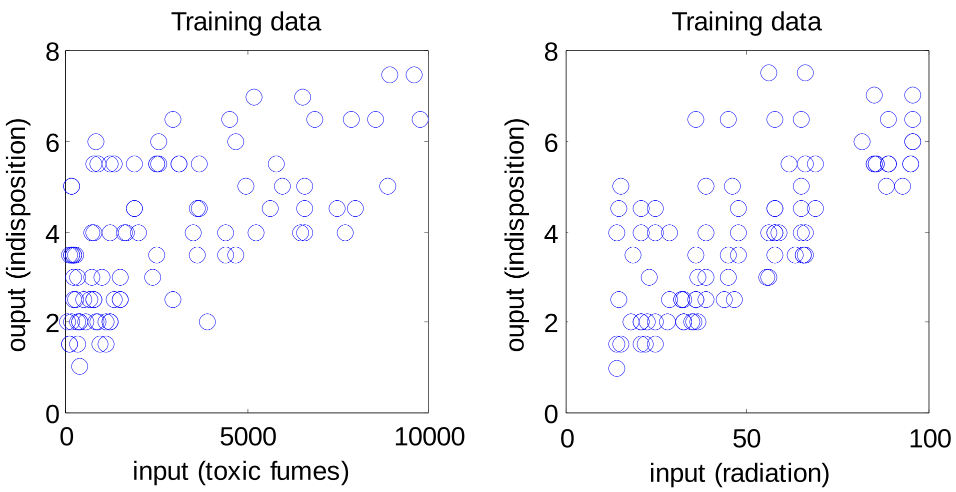

Figure 4: A scatter plot of the training data

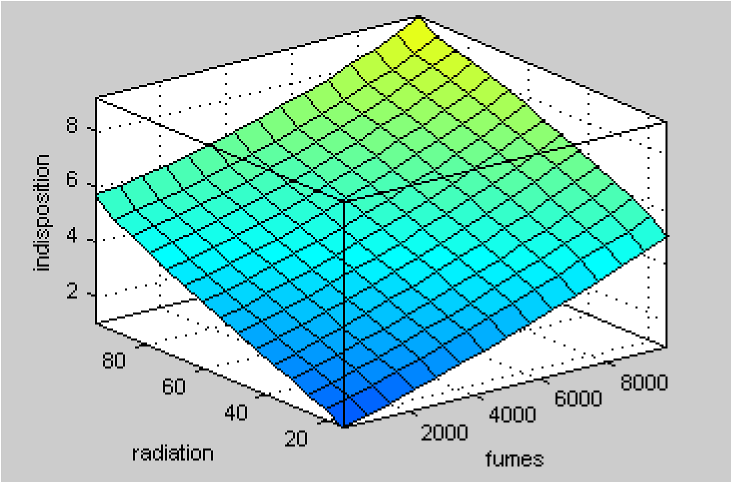

Figure 5: The ANFIS surface

4.2. Model Training

The method of trial and error was used in order to decide the type of membership function that best describes the model and provides the lowest error. An estimate of the root mean square error (RMSE) between observed and modeled values was computed for each trial, and the best structure was determined by considering a trade-off between the mean square error and the number of parameters involved in computation. The gauss2 membership function gave better results than the gauss, generalized bell, trapezoidal, zmf, pimf and triangular membership functions.

Also, the method of trial and error has been applied to choose the optimum number of membership functions for each input. The use of more membership functions increases the rules of the model according to the formula:

$$number\, of\ rules = number\, of\ MFs^{numberof\ inputs} \qquad (10)$$

After many trial and error attempts, the results have shown that the increase in the number of rules beyond 2 MFs decreases the accuracy of the model. Finally, two-membership functions of gauss2 shape were chosen for each input variable.

Once the ANFIS structure was identified, the parameters of the triangular MFs and the output constants were fitted using the hybrid learning algorithm [Jang, 10]. ANFIS applies a mixture of the least-squares method (for the consequent part of the rules) and the back-propagation gradient descent method (for the premise part of the rules) for training the Fuzzy Inference System (FIS) membership function parameters to emulate a given training data set. It also uses a checking data set for checking the model over fitting. Table 1 presents the ANFIS parameter types and their values.

Table 1: ANFIS parameter types and their values used for training

ANFIS parameter type	Value
MF type	Gauss2 function
Number of MFs	2
Output MF	Linear
Number of nodes	21
Number of linear parameters	12
Number of non-linear parameters	12
Total number of parameters	24
Number of training data pairs	96
Number of evaluating data pairs	24
Number of fuzzy rules	4

The model was tested many times using a different number of epochs. Finally, taking into consideration the root mean square error, the best results were obtained after 1000 epochs. After 1000 training epochs, the model was able to predict the total amount of indisposition based on the fumes and radiation. Figure 6 depicts the form of the initial membership functions of each input variable before the training of the model and the final membership function form after the completion of the training process.

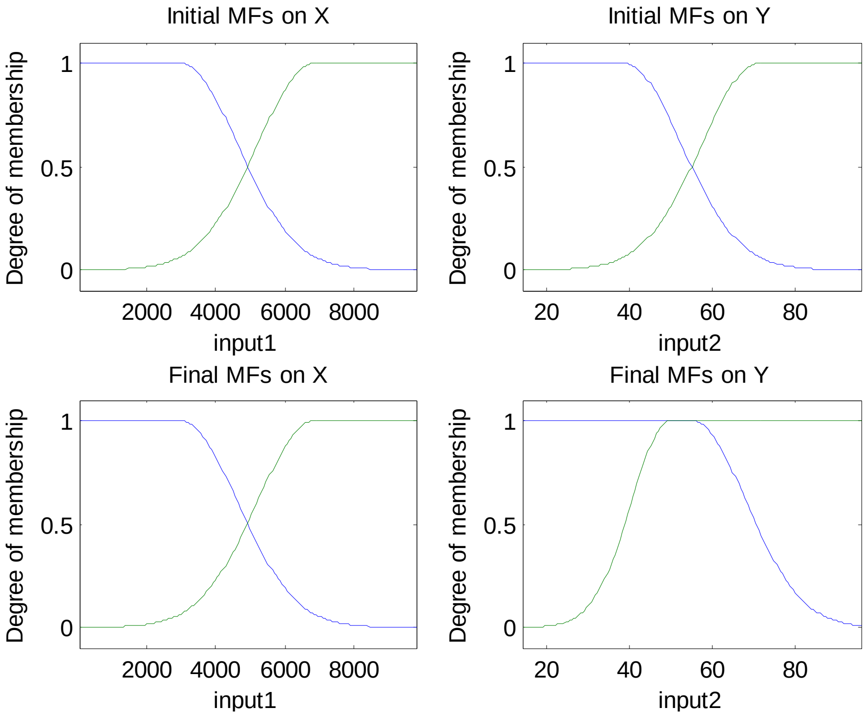

Figure 6: The form of the MFs before and after the training

The algorithm creates the following four rules (2^2 =4) according to formula (10):

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_1 and y is B_2, then $f_2 = p_1x + q_2y + r_2$

Rule 3: If x is A_2 and y is B_1, then $f_3 = p_2x + q_1y + r_3$

Rule 4: If x is A_2 and y is B_2, then $f_4 = p_2x + q_2y + r_4$

The linguistic interpretation of the above rules is as follows:

Rule 1: If toxic fumes are insignificant and radiation is insignificant then the indisposition is (1)

Rule 2: If toxic fumes are insignificant and radiation is significant then the indisposition is (2)

Rule 3: If toxic fumes are significant and radiation is insignificant then the indisposition is (3)

Rule 4: If toxic fumes are significant and radiation is very significant then the indisposition is (4)

The bullets 1, 2, 3 and 4 are the results of the formula after having been trained (f_1,f_2, ,f_3 *and* f_4). Figure 7 depicts a graphical representation of the fuzzy inference rule mechanism.

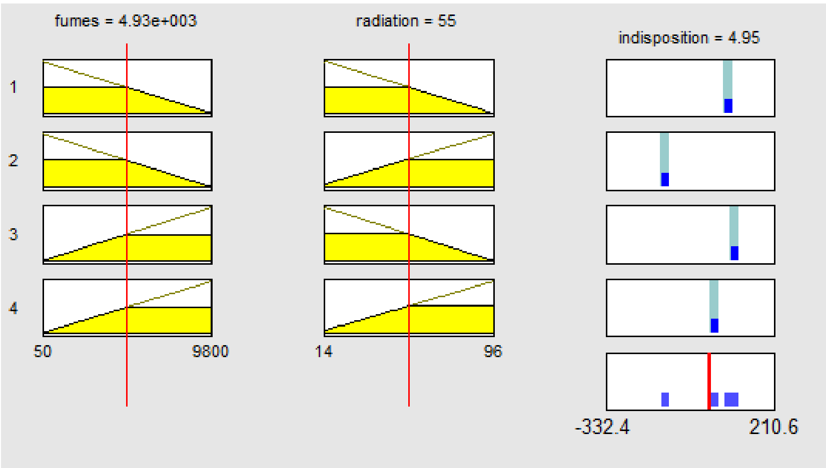

Figure 7: A view of the rule mechanism

As previously written, the aim of this study is to compare and analyse fuzzy logic and neural network approaches for setting up data-driven welders' risk forecasting models. To perform this experiment, the same input and output variables were considered for both approaches. So, the neural network model is parameterized with the same training data. By trial and error ranging between 3 and 25 neurons, the final NN architecture is characterized by two neurons in the input layer, 12 in the hidden layer and one in the output layer. However, the Levenberg Marquardt algorithm was used for training the model since it was characterized by a low number of inputs.

Results

Ninety six data samples were used to train the models. The remaining 24 samples that were not used during the training phase were fed into the models to evaluate their performance (out-of-sample evaluation). A graphical representation between actual values and ANFIS estimated values was illustrated in Figure 8, indicating the performance of the test data that were excluded from the building of the model. The blue line with square marks illustrates the observed values and the red line with asterisk marks illustrates the estimated values by ANFIS. Accordingly, Figure 9 depicts the graphical representation of the NN model.

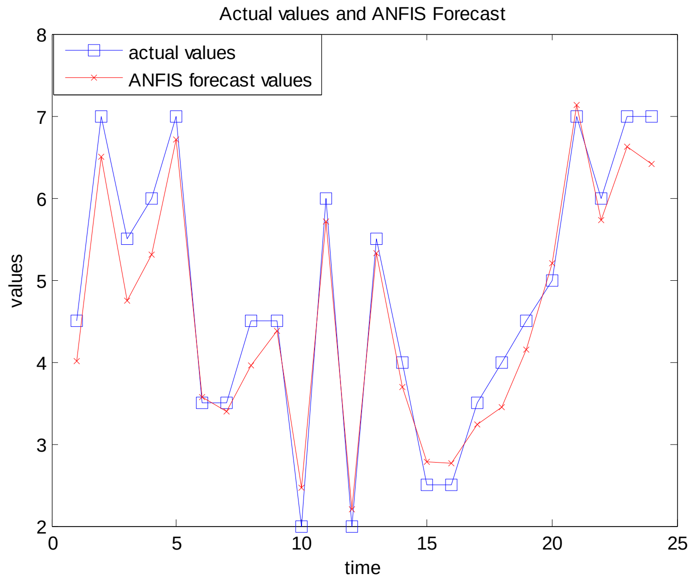

Figure 8: Actual values and ANFIS forecasts out-of-sample

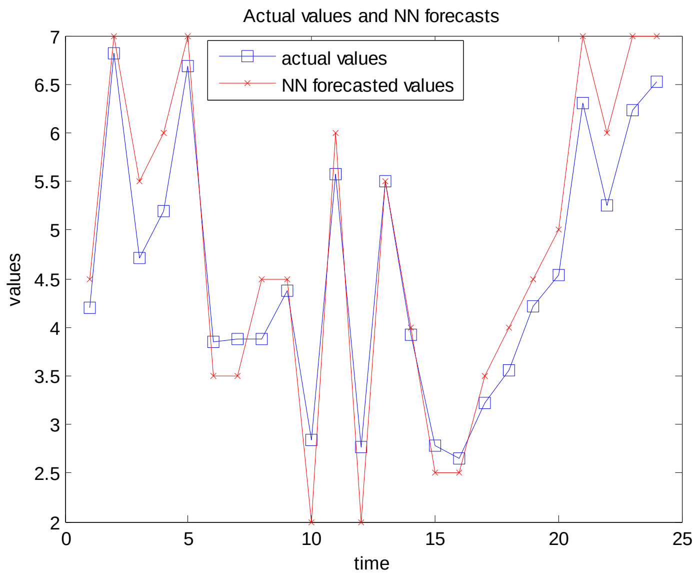

Figure 9: Actual values and NN forecasts out-of-sample

The performance of ANFIS and NN was assessed based on calculating four main types of errors: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The errors have been calculated for both approaches; Table 2 summarizes the error results.

Table 2: Forecasting results

Type of errors	**ANFIS**	**NN**
MSE	0.1524	0.4690
RMSE	0.3904	0.6848
MAE	0.3439	0.4810
MAPE	7.953	11.671

The ANFIS that minimized the four error measures (bold) described in the previous section was superior to the NN model. These results showed that the toxic fumes and the radiation in the training input data set were the key points in improving the indisposition forecasts. Other aspects, such as a more detailed collection of input variables, may be fundamental to improve the general quality of the forecasts. Moreover, it is well known that there are many limitations in the estimation of concentrations for toxic gases or radiation because of the unforgiving nature of the sensors involved. Hence, multiple sensors have been generally utilized to overcome the problems. However, it is expected that the limitations may be cleared to some extent even with only one sensor if more information or parameters are obtained from the sensor.

Furthermore, it is now worth stressing that while performing all the previous numerical experiments, some problems relating to the reliability of the ANFIS model must be mentioned. However, it has been noted that when this model is applied, the input training data set can lead to a rule system which is not able to furnish a result for each testing of input data. In other words, the input vectors do not satisfy any rules during the testing phase when the model uses the zmf and pimf membership functions, thereby making it impossible to execute the forecast. In particular, this proposed model was not able to execute a forecast in some testing cases since the input vectors do not satisfy any "IF" condition of the trained/calibrated rules for zmf and pimf MFs.

From a statistical viewpoint, the error values are not very low, but independently of the specific values of errors. Therefore, what is more important is that this model can forecast a satisfactory level of electrical welding workers' total indisposition and it is superior to the NN model.

6. Conclusion

This study addressed the problem of comparing two data-driven approaches (the ANFIS approach and the neural network approach), in terms of accuracy, reliability and capability of dealing with two input variables to forecast the risk of professional welders in terms of the total indisposition.

With regard to the accuracy, both models provide good accuracy when trained with the same data. Nevertheless, the accuracy was calculated based on the lowest error of four different very common statistical errors: MSE, RMSE, MAE, and MAPE. The error results show that the ANFIS model outperforms the NN approach.

As regards the reliability, it has been shown that the considered models present different levels of reliability. In particular, ANFIS was not able to forecast in some evaluation cases when the zmf and pimf are used, as explained in the previous section. In addition, the NN model has not presented this problem since, given its own architecture, for each input vector an output vector is always obtained through the transfer functions of the hidden layers.

As regards the capability to deal with the input information, there are no differences in both approaches.

Moreover, total indisposition levels can be accurately forecasted for the input variables (and their ranges) using an ANFIS approach. ANFIS is a model-free, easy-to-implement approach. In contrast to traditional forecasting methods, little training is needed to calculate the total indisposition predictions. Thus, it implements a single-fitting procedure to non-linear situations, without the need for establishing a formal model for the problem being resolved. Similarly, no a priori information was required to determine the empirical relationship between the explanatory and forecasted variables, and the method suitability is always tested a posteriori. Furthermore, the

transparent rule structure of ANFIS allows the researcher to extract information on the empirical relationship between the toxic fumes and the radiation over time and to provide concise explanations.
Despite the above advantages, the ANFIS must be implemented very carefully. The minimum number of data samples must be at least 100, and the number of model parameters should not exceed one fourth of the number of samples in the training sets, in order to avoid the risk of over-fitting and losing generality. A limitation also exists for the number of rules that can be implemented within the framework of an ANFIS model. Hence, it hasbeen shown that the accuracy of the model initially increases with the number of rules, but beyond a certain number, the accuracy of the model starts to decrease again. Therefore, all the latter considerations indicate that, given its very structure, the ANFIS approaches perform better when the physical phenomena considered are synthesized by both a limited number of variables and if-then logic statements.

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