FUZZY-NEURAL MODULES FOR EVALUATION OF TECHNOLOGICAL AND RELIABILITY CHARACTERISTICS IN INDUSTRIAL PRODUCTS

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Abstract. The present paper describes the development of a modular fuzzy-neural (FN) system, designated for practical application of fuzzy sets for determination of fuzzy membership functions. A NN-structure, possessing a back propagation learning algorithm, which is developed under monotonic function constraints, is applied for generation of fuzzy membership functions. The so-developed FN structures and the generated fuzzy membership functions are then applied for evaluation of technological and reliability characteristics, but also for revealing the relationships, existing between the properties of some particular industrial products (e.g., XPS thermal insulation boards, applied in construction industry).

Keywords: fuzzy-neural system, fuzzy membership functions, technological and reliability characteristics, relationships in industrial products properties

1. Introduction

The issues for practical application of Fuzzy Logic (FL) and fuzzy membership functions are still actual, since the sophisticated (mathematical) fuzzy relations are useful for specific research, but they often are too restrictive for a real industrial application [6, 8].

Lately, there has been some rapid advance in the application of Neural Networks (NN) and fuzzy sets, since considerable efforts of the engineers and scientists were focused on a creation and a development of *fuzzy and fuzzy-neural systems, designated for adaptive control and fault diagnosis, but also for modeling and prognosis of systems and/or process behavior* [2, 4, 7, 10].

The input-output pairs, which are used in hybrid Fuzzy-Neural (FN) systems are expressed as “IF – THEN” rules in the FL structure and relate respectively the fuzzy variables with inexact values [5, 8, 10]. The FN-structures became thus capable to create an approximation framework, that can be used for generalization of the “IF – THEN” rules through learning from examples (in accordance with the adaptive nature of the NN learning procedures) [1, 3, 9, 11].

The present paper describes the development of a modular FN-system, designated for practical application of fuzzy sets for determination of fuzzy membership functions. A NN structure, possessing a back propagation learning algorithm, which is developed under monotonic function constraints is applied for generation and modeling of fuzzy membership functions. The so-developed FN-structures, and respectively the generated fuzzy membership functions are then applied for evaluation of technological and reliability characteristics, as well as for revealing the relationships, existing between the properties of some particular industrial products (e.g., XPS thermal insulation boards, applied in construction industry).

2. Definition of fuzzy membership functions and development of NN modeling structure

The original basis for the fuzzy sets was to consider a fuzzy membership function $M_{Fy}(X)$, that is capable *to associate* the observations X, expressed as a vector variable $X = (x_1, \ldots, x_m)$ with a real value in the interval [0, 1], please see [6, 10].

The real issue, related to the practical application of the fuzzy sets, is to find out a fuzzy membership function $M_{Fy}(X)$, *in those cases, when the dimension of the variable* X *is relatively high.* Generally, the fuzzy membership functions are monotonic, and can respectively be defined by a monotonic interpolation curve, which passes through all the data points [6, 10].

One of the most serious problems, which must be solved prior to the fuzzy sets in a real (i.e., practical) situations, is the *lack of strict assumptions and/or sophisticated construction techniques*, that can be used by the reliability engineers. Therefore, the generation of fuzzy membership functions should be based on subjective judgments, developed for a particular problems domain.

A potential solution of this particular problem includes an application of NN interpolation techniques for generation and modeling of the fuzzy membership functions.

One of the most relevant NN-structures is the three-layered NN, implemented with a Back-propagation Least Mean Square (BPLMS) learning algorithm. The topology of such NN is shown in Figure 1.

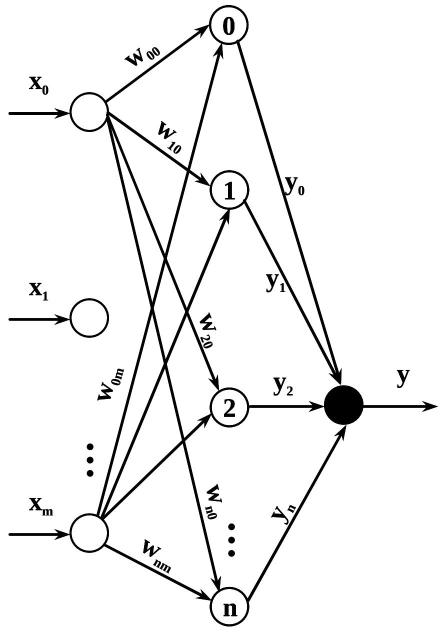

Figure 1. Topology of a three-layer NN with one hidden layer and a single output

The BPLMS learning algorithm is an integrative gradient descent algorithm, designed to minimize the mean square error between the actual output, generated by the NN, and the desired output of the structure, via a modification of the NN weights during the learning procedures. During the development of the BPLMS algorithm, each node (i.e., neuron) of the hidden layer in the NN structure operates with a sigmoid transfer function F(S), expressed by following relation:

$$F(S) = \{1 + \exp[- (S - \delta)]\}^{-1} \qquad (1)$$

where:

S is the sum of the weighted inputs to each node;

δ – the threshold (represented as an arbitrary non-zero number).

The so-created NN will perform a transformation of the data from the input vector **X**, to the output vector **Y**, i.e.,

$$\mathbf{Y} = \mathbf{M}\,(\mathbf{X}) \qquad (2)$$

The main goal here, consists in the determination of the *mapping function* **M**, which is capable to transform the *vector of conditions* (i.e., the inputs) **X**, to a *vector of the corresponding conclusions* (i.e., the outputs) **Y**, for some specific cause-effect relationships.

For this particular NN with a single output (presented in Figure 1) the relation is as follows:

$$y = \mathbf{M}\,(\mathbf{X}) \qquad (3)$$

where "y" is a scalar output function for the NN.

For the actual case, the single output node of the NN, expresses the property, that, the output "y" can represent only a single conclusion, generated by a fuzzy decision rule.

If there are "n" output nodes, that represent "N" functions (i.e., when multiple conclusions can exist), then, each of these "N" functions should respect-tively be represented by a single output node NN.

With respect to the NN-structure developed in Figure 1, and in accordance with relation (1), the output of the NN is

$$y = \left\{1 + \exp\left[-\left(\alpha_0 + \sum_{i=1}^{k} \alpha_i \cdot z_i\right)\right]\right\} \qquad (4)$$

where:

α_i is the threshold for the output node of the NN structure;

z_i, (i = 1, …, k) – the output of the i-th hidden node from the hidden layer of the NN.

With respect to relation (1), the output of i-th hidden node, may be determined as follows,

$$z_i = [1 + \exp\,(-W_i,\ X')]^{-1} \qquad (5)$$

where:

X is the input vector;

$W_i = (w_{i0}, w_{i1}, \ldots , w_{im})$ is i-th matrix of weights (please see again Figure 1).

The output of the NN can then be defined as follows

$$y = [1 + \exp[\alpha_0 + \sum_{i=1}^{k} z_i (1 + \exp(-W_i X'))^{-1})]\}^{-1}. \qquad (6)$$

For resolving some practical calculations issues, the vector components x_j can be normalized usually in the interval [0, 1] (via a linear transformation).

The *training process* of the NN uses a set of samples, obtained via functional mapping that can be learned by the NN (i.e., via the BPLMS algorithm), and usually represents an interpolation issue. When the learning process of the NN is accomplished (i.e., the NN structure has adopted the training set), the NN becomes capable to implement a particular function, which passes through the points, defined by the training sets.

In general, a NN-structure, with BPLMS algorithm, one hidden layer and sigmoid activation functions, is capable to approximate almost any continuous function [1, 7, 11].

The data set for each particular problem, can be represented as a pair [X, y], which must be capable to describe the relationships, existing between X and y. If such data are submitted to a NN, (with a BPLMS learning algorithm), then, the NN-structure should be able to learn these data and to generate a "fitting" function, of the form, described by equation (6), (under the condition, that the NN posses enough hidden nodes).

One of the objectives of the actual study, is to *generalize the knowledge*, represented by the individual production rules (expressed as fuzzy rules), rather then simply to rehearse these data, i.e., the FN-structure should be able to interpolate the data in an adequate way. In order to obtain a regular curve fitting, which is based on a limited number of training points, some heuristics knowledge should be applied.

For the actual case, the BPLMS shall be based on a monotonically selected constraints (during the execution of the learning process), so that a *monotonic function* could be generated. *In fact, the monotonic feature is one of the most important characteristics of the fuzzy membership functions* [5, 6, 8, 10], and could be defined as follows: "*y is monotonic in x_i*" if

$$[y\,(X \mid x_i = \beta_1) > y\,(X \mid x_i = \beta_2)] \qquad (7)$$

for [$\beta_1 > \beta_2$].

The relation (7) expresses a monotonic increasing function, and respectively, the fuzzy membership function (to be generated via the FN structure under BPLMS learning algorithm) shall also be monotonic.

The NN structure (please see Figure 1) applied for the generalization of the monotonic function, possesses three major features, which are related to the generation of a fuzzy membership function, and respectively are as follows:

a) In cases, when the NN learning procedures must be carried out under the restriction for monotonically development, the y function is also monotonic;
b) The y function must be continuous;
c) The y function has values in the open interval (0, 1), which practically means, that if the two extreme function values y_{max} and y_{min} can be defined, then the y function may be implemented through a learning process, in such a way, that the following relation can be valid,

$$0 < y_{min} \le y \le y_{max} < 1 \qquad (8)$$

It must be emphasized, that, an y function, which possess these three features, and respectively is implemented by such type of NN structure, represents in fact a *fuzzy membership function*. Still, the so-generated function however, is not a normal function, since the two extreme values y_{max} and y_{min} are not 1 and 0 respectively. The normalization of the y function can be developed via a simple mathematical rule for linear transformation, which has the following form,

$$y' = (y - y_{min}) / (y_{max} - y_{min}), \qquad (9)$$

so that $y' \in [0, 1]$.

Such normalization provides possibilities for all monotonic y-functions, generated by such type of NN structure, ***to serve as fuzzy membership functions.***

3. Development of algorithm for generation of fuzzy membership functions via BPLMS network

In many practical cases, there are some specific sets of process data, (obtained via practical studies, measurements, simulation, associative techniques, etc.,), that could be utilized for formulation of fuzzy functions. These fuzzy functions can, than be applied for generation of fuzzy decisions and concepts, and respectively applied in engineering practice (e.g., for adaptive control and supervision, for generation of final and complex decisions, for evaluation of process characteristics in industrial systems, etc.).

A particular kind of neural algorithm, (denoted as ***NEUMEM***) may therefore be developed, and respectively applied for analysis and evaluation of the different system's characteristics.

The stages of the developed "***NEUMEM***"-algorithm are as follows:

Stage 1. Analysis and verification of existing monotonic correlation between the input data X and the output(s) y. The verification should be based on the common knowledge about the existing relationships between these two variables. In cases, when this condition can not be satisfied – then a decomposition and/or a transformation of X must be performed. The result of these procedures is the generation of monotonic relationship.

Stage 2. Construction of a data set {DS}, in which each observation and/or measurement "d", must be a data point of the type $d(X, y) \in$ {DS}. For facilitation of the computations during the NN training, a normalization procedures on X, in the interval [0, 1], and on y, respectively in the interval $[y_{min}, y_{max}]$, should be performed. During the normalization process, the interval of values $[y_{min}, y_{max}]$ should be the desired range within the interval (0, 1).

Stage 3. Determination of particular sets $\{D_{SF}\}$ and $\{D_{IF}\}$, such that, $d \in \{D_{SF}\}$, if d is a superior frontier point of {DS}, and $d \in \{D_{IF}\}$, if d is a inferior frontier point of {DS}. The NN structure must therefore be trained via learning sets of the type $\{D_{SF}\}$ and $\{D_{IF}\}$ respectively, and under the condition of monotonic feature. As a result of the training, two specific fuzzy functions of the type $M_{SFy}(X)$ and $M_{IFy}(X)$ should be generated.

4. Application of the created FN-structures for evaluation of technological and reliability characteristics in industrial products

The so-developed FN structures (please, see Figure 1) are already capable to generalize fuzzy membership functions, on the basis of a human knowledge, and by using the **NEUMEM**-algorithm.

In many practical cases, the only existing preliminary knowledge (related to the generation of fuzzy membership functions) is the primary set of data, obtained during the practical realization of industrial products.

In Table 1 are generalized the so-called "raw" data, that are related to the practical realization of multi-layered XPS foam boards, designated for construction thermal insulation, and manufactured in a XPS manufacturing industrial complex, (located near the town of Varna, Bulgaria). The preference data for eight different types of products (i.e., of multi-layered boards) are available.

The main goal of this study, includes a determination of the fuzzy relationships, that may exist between the preferences of the consumers, and some specific criteria, (describing the technological and reliability characteristics of the products).

For this actual case, the particular set of criteria C_i, may be defined as follows:

- C_1 – density (kg/m^3);
- C_2 – tension pressure (kPa);
- C_3 – price per cubic meter (EU);
- C_4 – conductivity ($\times 10^{-3}$) - thermal insulation capacities for 10 ± 0.3^oC;
- C_5 – duration of exploitation (i.e., reliability resource), with full retention of the technological characteristics and the reliability properties, i.e., with no degradation occurred (months).

The so-obtained data (presented in Table 1), were based on the measurements and evaluation, performed under real exploitation conditions, as well as on some laboratory simulations.

A FN-structure is used for generation of a fuzzy function, that is capable to reveal the relationships between the structured criteria (i.e., from C_1 thru C_5).

The columns in Table 1, represent the original data on eight types of XPS products, as well as their ratings (R), which are respectively normalized to [0, 1], (for the training purposes).

Columns C_1 thru C_5 contain the original data, as well as the normalized ratings (N_{C1} thru N_{C5}), over the selected five criteria, that are considered during the evaluation of the XPS multilayered foam boards.

Table 1. Original data on 10 types of multi-layered XPS boards, applied for construction purposes

N^o	**Type**	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**Rank**
		N_{C1}	N_{C2}	N_{C3}	N_{C4}	N_{C5}	
1	A20	17.1	350	101	34	185	0.75
		0.58	0.65	0.66	0.55	0.60	
2	A30	17.3	350	101	35	183	0.70
		0.62	0.65	0.66	0.57	0.56	
3	A40	17.2	354	104	35	182	0.65
		0,60	0.60	0.72	0.57	0.54	
4	A50	17.4	360	104	37	187	0.55
		0.66	0.52	0.72	0.63	0.44	
5	A60	17.4	360	110	38	187	0.50
		0.66	0.52	0.88	0.68	0.44	
6	B5	16.8	355	103	34	183	0.45
		0.55	0.48	0.68	0.55	0.56	
7	B10	16.7	355	103	34	185	0.40
		0.45	0.48	0.68	0.55	0.60	
8	F4	15.6	350	101	37	182	0.30
		0.33	0.65	0.66	0.63	0.74	

Each row of Table 1 represents a training sample for the developed BPLMS network. For practical convenience, already transformed criteria values were used, in order to ensure, that the fuzzy functions would always be monotonically increasing. The last column of Table 1 represents the rank for each type of the XPS-product, which is expressed as normalized values, corresponding to the N^o, shown in the first column of Table 1. The so-determined values constitute the y-outputs of the neural structure, obtained via equation (6).

The developed NN contained 10 hidden nodes (neurons) in its hidden layer, and the learning process is performed via a BPLMS learning algorithm (developed under the requirements for monotonic restriction). Therefore, a generalization of the fuzzy functions was obtained.

The NN-structure was trained with about 2000 learning iterations. When the learning process has been completed, the NN was able to generate *fuzzy membership functions*, (represented by equation (6)), by using the weight matrixes, presented in Table 2. The so-developed application shows, that almost any kind of fuzzy function can be generated via monotonic NN model, but what is more important is, that the NN is also capable to provide some important fuzzy reasoning information.

Table 2. The NN weight matrixes for the fuzzy function, generated for the XPS-products

Nº	w_{i0}	w_{i1}	w_{i2}	w_{i3}	α_i
1	0.374	0.875	0.667	0.074	-2.256
2	1.076	0.946	0.588	0.899	-0.968
3	-1.259	0.971	-0.477	0.973	1.981
4	2.793	-0.045	0.299	0.911	-3.113
5	0.698	1.457	0.024	-0.214	-0.078
6	-1.659	2.651	0.051	0.534	2.145
7	1.244	1.024	0.782	0.498	3.182
8	-0765	0.039	0.964	0.337	1.883

In the cases when, the sales & management team of the production company wishes to know what could be the optimal application of each type of the already manufactured XPS multilayered boards, as well as of any possible new type of sub-product, the so-generated fuzzy function are capable to reveal the corresponding rank for each product.

For example, for an existing XPS-product of the type A50, the rank is 0.55, while for a new and ready to be developed product of the type A50+ (characterized by the following criteria values: C_1 = 17.48; C_2 = 363; C_3 = 106; C_4 = 36 and C_5 = 140), the rank, generated by the fuzzy function will be 0.565, i.e., the new product could successfully be developed and applied in real operation conditions.

5. Conclusions

5.1. An NN-modelling structure with BPLMS learning algorithm, one hidden layer and a single output, corresponding to *y*-function, which can be used as a fuzzy membership function, were developed in the present study**.**

5.2. A particular NEUMEM-algorithm, utilized for generation of fuzzy membership functions via BPLMS network was developed and applied for the purpose.

5.3. The so-developed NN structure, the NEUMEM-algorithm and respectively the generated fuzzy membership functions were applied for evaluation of technological and reliability characteristics of manufactured XPS-industrial products (multi-layer boards, applied for construction thermal insulation), and under real operation conditions.

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