An Innovative Artificial Neural Network Evaluation Model: Application in industry

L. S. Iliadis, S. Spartalis, S. I. Tachos
Democritus University of Thrace, Hellas
liliadis@fmenr.duth.gr

Abstract

Monitoring of processing elements values and overall performance is one of the most critical issues of an Artificial Neural Network development process. This should happen as the network evolves and it is the actual task that enables the developer to make informed decisions about the proper network topology, math functions, training times and learning parameters. This manuscript presents the framework of a new model that uses Fuzzy Logic in order to perform the crucial neural network validation task. It offers a new flexible approach that is capable of viewing this task under different perspectives. The model has been tested for a specific case study with actual data and a comparison to the existing methods is presented.

1. Introduction

The choice of an Artificial Neural Network's (ANN) optimal configuration is based on minimizing the differences between the ANN predicted values and the actual experimental data after a certain number of iterations. This is performed in both Training and Testing processes by using various diagnostic methods called instruments. The instruments provide the developer with diagnostic information that can be considered as indications of the ANN's good or poor performance. This paper presents the design and development principles and also the actual testing of a new ANN Evaluation Framework (NANNEF).

2. Typical ANN evaluation instruments

Two well known ANN instruments are the Root Mean Square Error (RMS Error) and the Confusion Matrix (CM) that incorporates the Common Mean Correlation. The RMS Error adds up the squares of the errors for each PE in the output layer, divides by the number of PEs in order to obtain an average and finally estimates the square root of that average. Hence the name root square. The squaring of the errors gets rid of the sign of the error but increases the magnitude. The square root is used in order to remove the magnitude. The RMS Error is a valuable and common measure of an ANN's performance.

The CM provides an advanced way of measuring an ANN's performance during the "learn" and "recall" phases. It allows the correlation of the actual output of an ANN to the desired results in a two dimensional visual graphical display [14][15]. This is achieved by providing the user with a graph consisting of numerous small cells called bins. The network with the optimal configuration must have the bins on the diagonal from the lower left to the upper right. In this way the CM can be considered as an instrument indicating how well the network is performing

An important aspect of the CM is that the value of the vertical axis (in the produced histogram) is the Common Mean Correlation (CMC) coefficient of the desired (d) and the actual (predicted) output (y) across the Epoch. The CMC is calculated by the following equation 1.

$$CMC = \frac{\sum\left(d_i - \bar{d}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum\left(d_i - \bar{d}\right)^2 \sum\left(y_i - \bar{y}\right)^2}} \quad (1)$$

where

$\bar{d} = \frac{1}{E}\sum_{1}^{n} d_i$ and $\bar{y} = \frac{1}{E}\sum_{1}^{n} y_i$

It should be clarified that *d* stands for the desired values, *y* for the predicted values where *i* ranges from 1 to *n* (the number of cases in the data training set) and *E* for the Epoch size, which is the number of training data sets presented in the ANN learning cycles among weight updates.

3. Materials and methods

The main title (on the first page) should begin 1-3/8 inches (3.49 cm) from the top edge of the page, centered, and in Times 14-point, boldface type. Capitalize the first letter of nouns, pronouns, verbs, adjectives, and adverbs; do not capitalize articles, coordinate conjunctions, or prepositions (unless the title begins with such a word). Leave two 12-point blank lines after the title.

3.1. Fuzzy Sets

According to Fuzzy Algebra (FA) each object x of the universe X belongs to a fuzzy set $\tilde{S}$ with respect to a characteristic real number $\mu_s(x)$ called Degree of Membership (DOM) that is $\tilde{S} \subseteq X$ *iff* $\tilde{S}=\{(x,\mu_s(x))/\mu_s: X\to[0,1]: x\to\mu_s(x)\}$[14].These, specific functions called Membership Functions (MF) are used to determine the DOM value (MV). For example, the Triangular Membership function (TRIAMF) is given by the following equation 2 [5], [10]. The Triangular Membership Values are also called "*first order indices*".

$$\mu_s(x;a,b,c) = \max\{\min\{\frac{x-a}{b-a},\frac{c-x}{c-b}\},0\} \qquad (2)$$

where a<b<c

Notice that, the only one point, where the DOM equals to 1, is x=c.

The following equation 3 presents the Trapezoidal Membership function (TRAPMF) [7].

$$\mu_s(x;a,b,c,d) = \max\{\min\{\frac{x-a}{b-a},1,\frac{d-x}{d-c}\},0\} \qquad (3)$$

where a<b<c<d

On the other hand, for each TRAPMF a tolerance [b,c] exists such that the DOM equals to one.

The following function 4 corresponds to a parametric form of the Sigmoid MF family [18].

$$f(x,a,c) = \frac{1}{1+e^{-a(x-c)}} \qquad (4)$$

It should be clarified that in the Sigmoid MF the parameters a and c determine its shape and position. Therefore by employing the above MFs a FS can be defined using the following equation 5 [8].

$$\tilde{S} = \left\{\left(x,\mu_{\tilde{S}}(\chi)\right)\right\} \qquad (5)$$

3.2. Conjunction on Fuzzy Sets

Conjunction and Aggregation of FS can be performed by applying instances of various T-Norms families [10]. The following equations 3.2.1 to 3.2.5 present five of the main T-Norm families of operations that perform Fuzzy Conjunction [16].

The Hamacher Family

$$\mu_{\left(\tilde{A}\cap\tilde{B}\right)} = \frac{\mu_{\tilde{A}}\mu_{\tilde{B}}}{\mu_{\tilde{A}}+\mu_{\tilde{B}}-\mu_{\tilde{A}}\mu_{\tilde{B}}+\alpha(1-\mu_{\tilde{A}}-\mu_{\tilde{B}}+\mu_{\tilde{A}}\mu_{\tilde{B}})} \qquad (6)$$

where a>0, with generators $\dfrac{\mu_{\tilde{A}}}{\mu_{\tilde{A}}+a(1-\mu_{\tilde{A}})}$

The Minimum Approach (7)

$$\mu_{\left(\tilde{A}\cap\tilde{B}\right)} = \left\{\left(x,\mu_{\tilde{A}\cap\tilde{B}}(\chi)\right)\backslash\mu_{\tilde{A}\cap\tilde{B}}(\chi)=\mu_{\tilde{A}}(\chi)\wedge\mu_{\tilde{B}}(\chi)=Min\left(\mu_{\tilde{A}}(\chi),\mu_{\tilde{B}}(\chi)\right)\right\}$$

The Algebraic Product

$$\mu_{\left(\tilde{A}\cap\tilde{B}\right)} = \mu_{\tilde{A}}(X)\,\mu_{\tilde{B}}(X) \qquad (8)$$

The Drastic Product

$$\mu_{\left(\tilde{A}\cap\tilde{B}\right)} = \text{Min}\{\mu_{\tilde{A}}(X),\mu_{\tilde{B}}(X)\}\ \textit{if}\ Max\{\mu_{\tilde{A}}(X),\mu_{\tilde{B}}(X)\}=1$$

else $\mu_{\left(\tilde{A}\cap\tilde{B}\right)} = 0$ (9)

The *Einstein Product*

$$\mu\left(\tilde{A}\cap\tilde{B}\right) = \frac{\mu_{\tilde{A}}\{X\}\mu_{\tilde{B}}(X)}{2-[\mu_{\tilde{A}}\{X\}+\mu_{\tilde{B}}(X)-\mu_{\tilde{A}}\{X\}\mu_{\tilde{B}}(X)]} \qquad (10)$$

There exist many other T-Norm families like the *Aczel-Alsina*, the *Jane Doe1,* the *Jane Doe 1 – Hamacher*, the *Schweizer*, the *Dombi* and finally the *Frank* family [16]. Of course a good question would be the choice of the proper T-Norm. The answer is not obvious [10]. Each T-Norm offers a good approach and it sees things under a different perspective. Other T-Norms can be characterized as optimistic whereas others as pessimistic and others assign a case a high degree of membership when one or more parameters have extreme values [10]. For example according to the MIN Norm, the minimum DOM is the conjunction result whereas the Einstein and the Hamacher Products consider all of the factors equally [10].

If we consider the above T-Norms as aggregation functions Agg(x) then we can have multiple attribute decision making with unequal weights for attributes [2], [3], [19].

$$\mu_{\tilde{S}}(x_i) = Agg\left(f\left(\mu_{\tilde{A}}(x_i), w_1 \right), f\left(\mu_{\tilde{A}}(x_i), w_2 \right), \ldots\ldots f\left(\mu_{\tilde{A}}(x_i), w_n \right) \right) \quad (11)$$

where i=1,2…..k and k is the number of cases and n is the number of the attributes [5].

The function f is defined as follows: $f(a,w) = a^{\frac{1}{w}}$ (12)

Note that $\lim \frac{1}{0^+} = +\infty$ so that w can be equal to zero.

In this way the attributes can be considered as having different contribution in the estimation of the conjunction DOM and various scenarios can be performed.

Also Alpha-cuts are used to estimate the number of cases that belong to a FS with a DOM higher than or equal to a specific value. An Alpha-cut of the membership function A (denoted aA) is the set of all x such that A(x) is greater than or equal to alpha a. Similarly, a strong alpha-cut (denoted a + A) is the set of all x such that A(x) is strictly greater than alpha a. Mathematically, the following equations 13 and 14 are used to define an aA and an a+A.

aA={x|A(x)≥a} (13)

a + A = {x | A(x) > a} (14)

4. A new ANN validation framework

In both Training and Testing processes, the output of the ANN can be considered as an nxm table (two dimensional matrix) where n is the number of used cases (data records) and m is the number of Processing Elements (PE) in the output layer. The following table OUT presents the structure of an ANN potential output. In this case there also exists another similar table called DES with the actual (desired) values for the output neurons.

$$\text{OUT} = \begin{bmatrix} O_1 & Y_1 & .... & Z_1 \\ O_2 & Y_2 & .... & Z_2 \\ .... & ..... & .... & .... \\ O_n & Y_n & .... & Z_n \end{bmatrix}$$

$$\text{DES} = \begin{bmatrix} D_{O1} & D_{Y1} & .... & D_{Z1} \\ D_{O2} & D_{Y2} & .... & D_{Z2} \\ .... & ..... & .... & .... \\ D_{On} & D_{Yn} & .... & D_{Zn} \end{bmatrix}$$

The final target is the minimization of the differences $d_{1i} = O_i - D_{Oi}$, $d_{2i} = Y_i - D_{Yi}$, ...$D_{mi} = Z_i - D_{Zi}$ where i=1,….., n and the number of differences equals to m.

This paper proposes a new innovative model that can be used to evaluate the performance of an ANN. According to this model, nXm Fuzzy Sets can be formulated and defined. Each Fuzzy Set corresponds to a desired value of the ANN. Each output neuron is assigned a vector of Fuzzy Sets of the following type:
VD_1= {FS_1 ="Values equal to D_{O1}", FS_2 = "Values equal to D_{O2}", ……, FS_n = "Values equal to D_{On}"}.
This can be also denoted as follows:
VD_1= {$FS_1 = (O_1, \mu_1)$, $FS_2 = (O_2, \mu_2)$, ………, $FS_n = (O_n, \mu_n)$}.

This means that if the ANN has m neurons in the output layer, m such Vectors of Fuzzy Sets VD_1, VD_2, ….., VD_m will be formed. Each element D_{Oi} of the DES (Desired Matrix) has its corresponding FS VD_i and each element O_i of the ANN output Matrix belongs to the FS VD_i with a Degree of Membership μ_i.

The Degree of Membership of each output value to its corresponding FS can be estimated using the Triangular and with the Trapezoidal MF 3.1.1 and 3.1.2 which constitute the NANNEF's Individual Triangular Membership Values (ITRIMV) and the NANNEF's Individual Trapezoidal Membership Values (ITRAMV). Thus from the ITRIMV and from the ITRAMV we obtain the Trapezoidal Mean Membership (TRAMM) and the Triangular Mean Membership (TRIMM). Finally the Trapezoidal Mean Error=1-TRAMM and the Triangular Mean Error=1-TRIMM is a good overall error estimator. The following figures 1 and 2 present clearly the application of the TRIAMF in the ANN output Matrix. The most important aspect of all is the fact that the Fuzzy T-Norms can be applied as conjunction operators (with equal or with uneven weights) when the output Layer contains more than one neuron. In this case the TRAMM and the TRIMM corresponding to each neuron can be added to the TRAMM and to the TRIMM of another neuron and the Overall Mean Membership (OMM) is produced. This can be performed under different perspectives depending on the logic of each T-Norm.

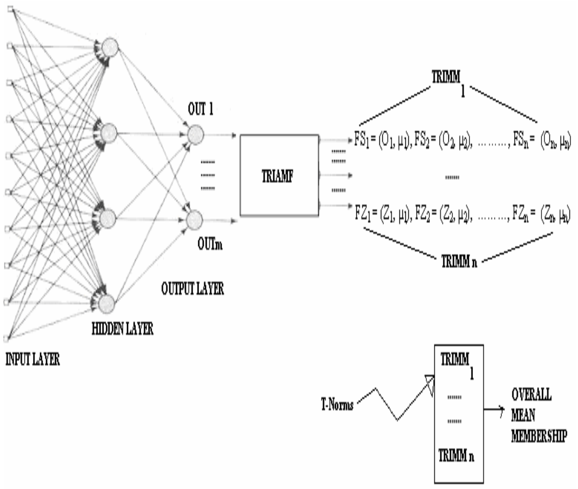

Figure 1: A single application of the TRIAMF on the output Matrix

In the case of the TRIAMF the value c that corresponds to the maximum Membership value of 1 is equal to the desired value D_{Oi}. The following figure 2 makes a graphical display of the TRIAMF application on the ANN output Matrix after the completion of an iteration.

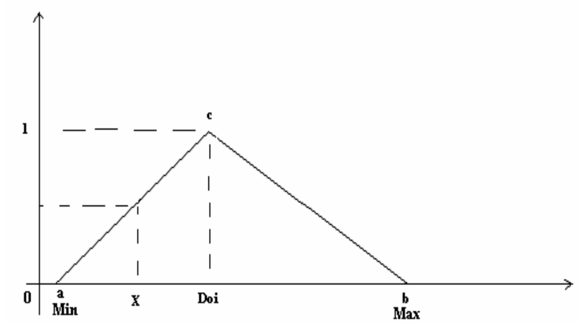

Figure 2: Application of the TRIAMF for an element of the ANN output Matrix

It should be clarified that in the TRIAMF equation a should be equal to 0, X should be equal to an output value of the OUT matrix, c should be equal to an actual value of the Desired matrix and b is a value much higher than the desired one after which the DOM is equal to 0. The definition of the Linguistic "much higher than" [9].

5. Application of NANNEF in wood industry

5.1. Estimating Loss factor

The NANNEF has been tested for the wood dielectric properties prediction which is an important task of wood industry [1]. More specifically an artificial neural network that can predict the dielectric properties of wood has been developed and tested by our research team using actual experimental data [1]. The optimal ANN is capable of accurately predicting the loss factor of two wood species not only as a function of ambient electro-thermal conditions but also as a function of basic wood chemistry. Thus, an important predictive tool has been created that allows optimization of dielectric heating and drying for many wood species without significant experimentation. Of course their chemical composition should be known under variable temperatures, moisture contents and electric field characteristics. In wood, radio frequency vacuum drying [11], [12], [13] and other high frequency electric field heating applications such as veneer and finger-joint gluing and parallam manufacturing [17], the knowledge of the fundamental dielectric properties of the material such as dielectric constant (ε'), loss tangent ($tan\delta$) and loss factor (ε'') are imperative in process design, control, optimization and simulation.

Table 1. A small sample of MV and NANNEF's evaluation in ANN testing

ANN Loss factor	Actual Loss factor	NANNEF's Individual Trapezoidal Membership Values	NANNEF's Individual Triangular Membership Values
0.00189	0.001856	0.99371819	0.9937119
0.00312	0.003181	0.98603476	0.9712535
0.00386	0.003979	0.97249853	0.9592466
0.00458	0.004659	0.99087918	0.9780556
0.00192	0.001979	0.9564435	0.9358696
0.00349	0.003375	0.97045024	0.9704218
0.00448	0.004309	0.94217161	0.9421124
0.00539	0.005131	0.87862632	0.8785178
0.00202	0.002126	0.91896647	0.900656
0.00359	0.003632	0.99776085	0.9836766
0.00461	0.00474	0.97726772	0.9646835
0.00575	0.005703	1	0.9698718
0.00262	0.00237	0.9489066	0.9489066
0.00405	0.004026	1	0.9925857
0.00529	0.005288	1	0.9989873

During the development of the ANN eleven variables have been used as inputs, including: the percentage of glucose (GLU), mannose (MAN), xylose (XYL), galactose (GAL), arabinose (ARA), lignin (LIG), extractives (EXTR), density, moisture content, voltage, and temperature. Only one variable was used as an output, namely, dielectric loss factor [1].

The above Table 1 shows the optimal ANN's output, the desired Loss factor values and the NANNEF evaluation output using the TRIAMF and the TRAPMF. Only in two cases the DOM are equal to 0 which means that the optimal ANN has very bad performance in these two predictions. On the other hand due to the tolerance interval the TRAPMF characterizes the ANN as having perfect performance in more cases than the TRIAMF.

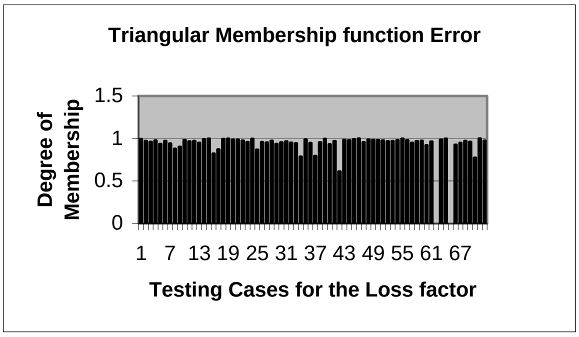

Figure 3. Evaluation of ANN in testing with TRIAMF

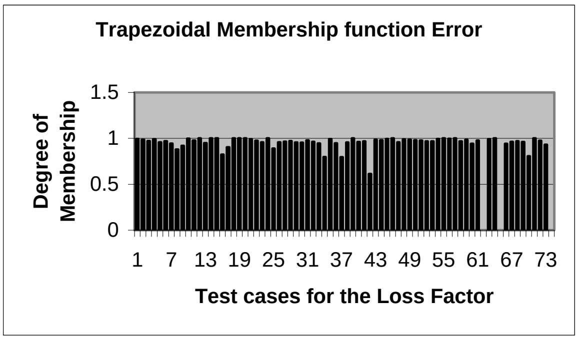

Figure 4. Evaluation of ANN in testing with TRAPMF

It is clearly shown in table 1 that in the case of the first ANN, the Trapezoidal Mean Membership (TRAPMM) is very high in the testing phase regardless the MF used. However table 2 shows that the TRAPMF produces a TRAPMM equal to 0.930975764 which is higher than the TRIAMF's 0.923964354. Also both the Trapezoidal Mean Error and the Triangular Mean Error have quite low values and they are equal to 0.069024 and 0.076036 respectively. Finally 13 cases have the highest MV of 1 using the TRAPMF whereas only one case has a MV of 1 using the TRIAMF.

Table 2. Mean Errors and a-cuts

Trapezoidal Mean Error	**Triangular Mean Error**
0.069024	0.076036
Trapezoidal Mean Membership	**Triangular Mean Membership**
0.930975764	0.923964354
Triangular a-cuts aA	**Trapezoidal a-cuts aA**
MV =0 Number of cases **2**	MV=0 Number of cases **2**
MV interval = [0-0.5] Number of cases **0**	MV interval = [0-0.5] Number of cases **0**
MV interval = (0.5-0.7] Number of cases **1**	MV interval = (0.5-0.7] Number of cases **1**
MV interval = (0.7-0.8] Number of cases **3**	MV interval = (0.7-0.8] Number of cases **3**
MV interval = (0.8-0.9] Number of cases **4**	MV interval = (0.8-0.9] Number of cases **4**
MV interval = (0.9-1) Number of cases **61**	MV interval = (0.9-1) Number of cases **49**
MV= 1 Number of cases **1**	MV = 1 Number of cases **13**
72 cases	**72 cases**

6. Employing NANNEF for ANN that estimate two parameters

The bending strength and stiffness, numerically represented by the Modulus of Rupture (MOR) and Modulus of Elasticity (MOE), are arguably the two most important mechanical properties of wood. These flexural properties have been shown to exhibit strong correlations with several inherent wood properties [1]. For instance, both bending stiffness and strength increase with density and decrease when moisture content and MFA increase [4].

An ANN has been developed towards MOR and MOE estimation. The input layer consisted of four neurons corresponding to the four input variables, including Density, Moisture Content, MFA, I_{CV} and forest type and the output Layer consisted of two neurons corresponding to the two output parameters MOR and MOE. It should be clarified that I_{CV} is the coefficient of variation of azimuthal intensity profile which represents the standard deviation of intensity when the azimuthal diffraction profile (including background scattering) is normalized to an average intensity of unity [6] as per Equation 15.

$$I_{CV}^2 = \frac{1}{2\pi}\int_0^{2\pi}(I(\phi)-1)^2\,d\phi \tag{15}$$

The optimal ANN used the Back Propagation Optimization algorithm, the Tangent Hyperbolic Transfer function and the Extended Delta Bar Delta Learning Rule, whereas the Hidden Layer had two sub-Layers each comprising of 10 neurons. Using the traditional evaluation methods the developed ANN had RMS Error equal to 0.2726 and R^2 =0.5150 for MOR whereas R^2 =0.6500 for MOE in the testing phase that determines generalization ability.

Using NANNEF the main advantage is that we can obtain two vectors of Separate Performance Indices and also a Unified Performance Index that is an overall performance evaluator.

Table 3. Actual and ANN values and NANNEF's evaluation for MOE

Actual MOE values	ANN MOE values	NANNEF's Individual Trapezoidal Membership Values for MOE	NANNEF's Individual Triangular Membership Values
11162.5	14540.89	0.609774	0.60175
12497.1	14536.13	0.727479	0.714761
13268.6	16706.19	0.470734	0.46094
12978	15433.15	0.64432	0.631779
12993.3	14492.61	0.790049	0.774618
13499.4	15446.71	0.698511	0.683169
18113.3	15087.81	0.579837	0.564727
19167.5	15395.65	0.541787	0.528814
19100.8	15646.8	0.578822	0.564894
14706.7	14571.36	1	0.961812
13073.8	13544.87	0.947162	0.92832
13490.4	15370.85	0.710057	0.694495
14248.6	13446.73	0.775995	0.740167
13967.3	15404.03	0.765817	0.74698
17015.7	15905.55	0.834597	0.810335
15540.2	15868.55	0.956216	0.92002
12634	14502.53	0.746968	0.733509
15479.3	15414.69	1	0.985033
14007.1	14952.48	0.853539	0.832335

The above Table 3 and the following Table 4 present a small sample of the ANN's evaluation for the cases of MOE and MOR estimation using the Trapezoidal and the Triangular Membership functions. The Degree of Membership equal to one is the perfect evaluation index. The following Table 5, presents the overall DOM which serves as the final ANN evaluation index for both of the estimated parameters MOE and MOR. The fact that numerous Evaluation indices are produced is an advantage of the model that offers different evaluation approaches under various perspectives.

Table 4. Actual and ANN values and NANNEF's evaluation for MOR

Actual MOR values	ANN MOR values	NANNEF's Individual Trapezoidal Membership Values for MOR	NANNEF's Individual Triangular Membership Values for MOR
73.13655	74.56785	0.967768	0.936236
68.72508	74.87505	0.791268	0.771021
81.29023	84.78143	0.801316	0.755742
60.3629	80.11546	0.446832	0.439174
79.38127	78.19641	0.987669	0.96355
77.54022	80.00497	0.902167	0.863396
83.83874	76.97003	0.833073	0.814178
88.45072	79.22047	0.794901	0.77799
84.4025	79.89063	0.900014	0.879772
77.36379	75.49725	0.963221	0.93878
66.44044	72.85275	0.798167	0.77997
52.71937	71.2153	0.575576	0.568497
51.00478	63.74026	0.722581	0.714314
59.04941	74.65203	0.58234	0.572928
74.17541	74.52218	1	0.983802
68.05146	73.74924	0.813147	0.793048
60.52219	68.78273	0.777823	0.764396
72.87583	73.21088	1	0.985245
62.75246	71.3038	0.753945	0.739534

Table 5: NANNEF instruments application for aggregation between two parameters

UNIFIED Overall DOM (Evaluation index) for MOE and MOR			
Minimum T-Norm		**Einstein T-Norm**	
Triangular MF	*Trapezoidal MF*	*Triangular MF*	*Trapezoidal MF*
0.422281523	0.431234864	0.572352898	0.610112
Drastic Product		**Hamacher Product**	
		Triangular MF	*Trapezoidal MF*
0.100895426		0.572353	0.61011165
Traditional instruments values			
MOR R^2=0.5150		MOE R^2=0.6500	

7. Discussion

Using the traditional evaluation methods in the case of the Loss Factor ANN, the *RMS Error* was equal to 0.0382 and the R^2 was equal to *0.9945*. The NANNEF's results agree with the ones of the traditional methods and they prove that the optimal ANN that was developed by Avramidis et al. 2006, has a reliable performance.

Furthermore the NANNEF offers an *aA* analysis that makes a very clear presentation of the ANN's performance categorization. Using the *aA* analysis we know how in many cases we have total agreement between the ANN and the desired values and in how many cases we have high, low and average agreement. Another very important achievement of the NANNEF is the fact that it produces both a vector of SPI that offer a clearer view of the network's performance for each case and also a UPI for an ANN which includes more than one processing elements in the output level. The fact that the ANN's UPI estimation is done under many different perspectives (due to the different nature of the T-Norms Aggregation functions) is very important and it offers a modern and flexible approach towards ANN evaluation.

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