International Journal of Computational Intelligence and Applications
Vol. 9, No. 2 (2010) 137–152
© Imperial College Press
DOI: 10.1142/S1469026810002823

DESIGN OF EXPERIMENTS IN NEURO-FUZZY SYSTEMS

CLEBER ZANCHETTIN

Federal University of Pernambuco, Center for Informatics, Cidade Universitária, Recife — PE, 50.732-970, Brazil

LEANDRO L. MINKU

University of Birmingham, School of Computer Science, Birmingham B15 2TT, United Kingdom

TERESA B. LUDERMIR

Federal University of Pernambuco, Center for Informatics, Cidade Universitária, Recife — PE, 50.732-970, Brazil
tbl@cin.ufpe.br

Received 9 September 2009
Revised 23 February 2010

Interest in hybrid methods that combine artificial neural networks and fuzzy inference systems has grown in recent years. These systems are robust solutions that search for representations of domain knowledge, reasoning on uncertainty, automatic learning and adaptation. However, the design and definition of the parameter effectiveness of such systems is still a hard task. In the present work, we perform a statistical analysis to verify interactions and interrelations between parameters in the design of neuro-fuzzy systems. The analysis is carried out using a powerful statistical tool, namely, Design of Experiments (DOE), in two neuro-fuzzy models — Adaptive Neuro Fuzzy Inference System (ANFIS) and Evolving Fuzzy Neural Networks (EFuNN). The results show that, for ANFIS, input MFs number and output MFs shape are usually the factors with the largest influence on the system's RMSE. For EFFuNN, the MF shape and the interaction between MF shape and number usually have the largest effect size.

Keywords: Neuro Fuzzy Systems; Design of Experiments; Adaptive Neuro Fuzzy Inference System; Evolving Fuzzy Neural Networks.

1. Introduction

The complexity and the dynamism of real world problems require sophisticated methods and tools for the construction of knowledge systems that can be used in the solution to such problems. The search for systems that can solve increasingly complex problems has stimulated research in a number of scientific fields, especially Hybrid Intelligent Systems. This area seeks to combine different techniques of learning and adaptation to overcome their individual limitations. Among such systems, one important model — Neuro-Fuzzy Systems — is an approach that can learn from the environment and then reason about its state. A neuro-fuzzy system is based on a fuzzy inference system, which is trained by a learning algorithm derived from artificial neural network theory. While the learning capability is an advantage provided by artificial neural network, the formation of a linguistic rule base is an advantage provided by the fuzzy inference system.

Intelligent systems have presented promising results in the solution of many complex problems. However, many problems are by nature imprecise, nonlinear and contain features that are altered by variations in the environment.[2] As conventional methods used in the construction of intelligent systems are generally non-adaptive and rigid, hybrid systems only obtain adequate results on specific points and under certain problem circumstances. Thus, the adaptability and instability of the problem require constant system re-configurations, such that they are used in situations where the operational points of the problem appear in different ways.[6]

The problem regarding the topology and parametric configuration of neuro-fuzzy systems worsens when we consider that many of the parameters are fuzzy variables and that these systems often operate in real time. The determination of network parameters is a difficult design task. Such parameters include membership functions, number and shape of each input variable, learning rates, an efficient technique for determining the initial rule base and fuzzy operators. Even in models that construct the rule base automatically, the performance of the system still depends on the careful selection of the sensitivity threshold, error threshold and learning rates.

The tuning and configuration of most intelligent systems are accomplished empirically based on a trial and error process. As shown in papers dealing with real applications, the designer has to select the topology and parameters to be used in each phase of the system design empirically, and this decision is usually taken in terms of the most common parameters, operators and membership functions performed.

Thus, it is very important to determine which factors have the greatest influence on the behavior and performance of the neuro-fuzzy system. The designer or the automatic parameter optimization method should therefore pay close attention to the selection of the most statistically significant parameters. In the present work, we perform a statistical analysis to verify the interactions and interrelations between variables in the design of neuro-fuzzy systems and to verify the most relevant factors in the design of such systems. This analysis was proposed in Zanchettin *et al.* (2005) and this work extends the main concepts of the methodology. The method used to perform the analysis is the Design of Experiments (DOE).[3] DOE has been successfully used in several areas for parameter estimation.[11–13] Experiments with two neuro-fuzzy systems — Adaptive Neuro Fuzzy Inference System (ANFIS)[4] and Evolving Fuzzy Neural Networks (EFuNNs)[5] — are performed with four different prediction and classification problems. The prediction databases used were the chaotic Mackey–Glass time series[1] and the Gas Furnace time-series.[7] The classification problems were Wine Recognition[10] and Fisher Iris.[8]

This paper is divided into five sections. Section 2 presents details of the neuro-fuzzy models. Section 3 describes the design of experiment methodology. Section 4 presents the results of the statistical experiment. Section 5 contains a summary of the paper.

2. Background

2.1. *Adaptive neuro fuzzy inference system*

ANFIS was perhaps the first integrated hybrid neuro-fuzzy model and belongs to the class of rule-extracting systems using a decompositional strategy, where rules are extracted at the level of individual nodes within the neural network. After extraction, rules are aggregated to form global behavior descriptions.

The ANFIS architecture consists of a five-layer structure, presented in Fig. 1. In the first layer, the node output is the degree to which the given input satisfies the linguistic label associated to the membership functions. The parameters in the first layer are referred to as premise parameters.

In the second layer, each node function computes the firing strength of the associated rule. In general, any T-norm operators that perform fuzzy AND can be used as the node function in this layer. Each node i in third layer calculates the ratio of the ith rule firing strength for the sum of firing strength of all rules. The fourth layer is the product of the normalized firing level and the individual

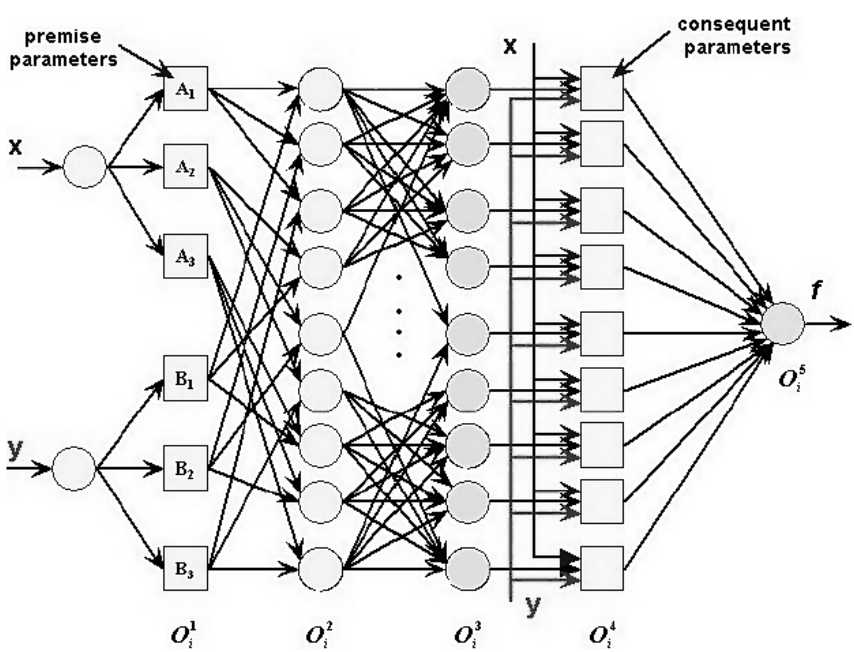

Fig. 1. ANFIS system.

rule output of the corresponding rule. Parameters in this layer are referred to as consequent parameters.

The single node function of the fifth layer computes the overall system output as the sum of all incoming signals. Note that only Layer 1 and Layer 4 contain modifiable parameters. Learning or adjustment of these parameters is a two-step process. First, while holding the premise parameters fixed, information is propagated forward in the network to Layer 4, where the consequent parameters are identified by a least-squares estimator. Next, in the backward phase, the consequent parameters are held fixed while the error is propagated and the premise parameters are modified using gradient descent.

The ANFIS algorithm used in the experiments was adapted from.[4] There are many possibilities for the choice of the basic parameters in the design of this neuro-fuzzy system: (1) number of inputs and outputs; (2) choice of a nonlinear function within the input neurons; (3) membership functions (triangular, trapezoidal, etc.) to represent a linguistic value; (4) defuzzifier method; (5) conjunction and disjunction operators; (6) initial step size; and (7) training epochs.

2.2. *Evolving fuzzy neural networks*

EFuNNs are neural networks that perform a set of fuzzy rules and a fuzzy inference machine in a connectionist way. An EFuNN is a connectionist system that facilitates learning from data, reasoning over fuzzy rules, aggregation, rule insertion and rule extraction. The system operates in an on-line mode and learns incrementally through locally tuned elements. It grows as data arrive and regularly shrinks either through node pruning or through node aggregation. EFuNN is an architecture that can classify multiple classes. Moreover, if a new class is added through training, EFuNN can automatically evolve a new output to reflect the change in the data set.

EFuNNs have a five-layer structure, presented in Fig. 2. Each input variable is represented by a group of spatially arranged neurons to represent a fuzzy quantization of this variable. Fuzzy quantization in variable space is represented in the second layer of nodes. Different membership functions (MF) can be attached to these neurons (triangular, Gaussian, etc.). The nodes representing membership functions can be modified during learning.

The third layer contains rule nodes that evolve through hybrid supervised/unsupervised learning. The rule nodes represent prototypes of input-output data associations, graphically represented as an association of hyper-spheres from the fuzzy input and fuzzy output spaces. Each rule node r is defined by two vectors of connection weights — $W_1(r)$ and $W_2(r)$ — the latter of which is adjusted through supervised learning based on the output error and the former is adjusted through unsupervised learning based on a similarity measure within a local area of the input problem space.

The fourth layer of neurons represents fuzzy quantification for the output variables in a similar manner as the input fuzzy neuron representation. The fifth layer

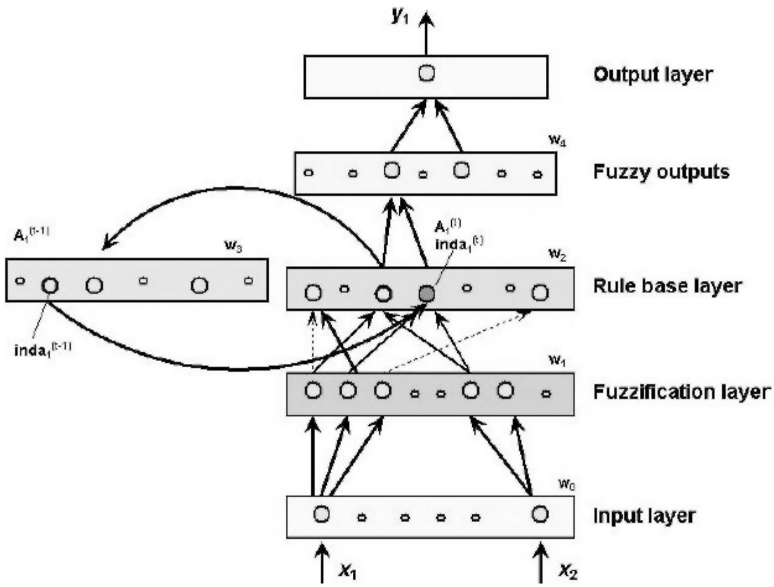

Fig. 2. EFuNN system.

represents the real values for the output variables. In the case of "one-of-n" EFuNNs, the maximum activation of the rule node is propagated to the next level. In the case of "many-of-n" mode, the activation values of m ($m > 1$) rule nodes that are above an activation threshold are propagated further in the connectionist structure.

EFuNN evolving algorithm used in our experimentation was adapted from Ref. 5 and is based upon the principle that rule nodes only exist if they are needed. As each training example is presented, the activation values of the nodes in the rule and action layers are examined along with the error over the action nodes. If the maximum rule node activation is below a set threshold (the Sensitivity Threshold), then a rule node is added. If the action node error is above a threshold value (the Error Threshold), a rule node is added. Finally, if the radius of the updated node is above a radius threshold (Maximum Radius), then the updating process is terminated and a rule node is added.

EFuNN has several parameters that need to be optimized according to the dataset used. These include: (1) number of inputs and outputs; (2) learning rate for W_1 and W_2; (3) pruning control; (4) aggregation control; (5) number of membership functions; (6) shape of membership functions; (7) initial sensitivity threshold; (8) maximum radius; (9) error threshold; and (11) m-of-n value.

3. Statistical Methodology

Experimental design theory is a branch of statistics that provides the researcher with numerous methods for selecting the independent variable values in which a limited number of experiments will be conducted. The various experimental design methods create certain combinations of numerical experiments (analysis) in which the independent variables are prescribed at specific values or levels. The results of these planned experiments are used to investigate the sensitivity of a dependent quantity — identified as the response — to the independent variables. Each analysis is an experimental run. In each run, factors are set to specific values within their respective ranges and responses of one or more variables are recorded.

Prior to experimental design, the allowable range of each of the k variables is defined by lower and upper bounds. The allowable range is then discretized at equally-spaced levels. The range of each variable is scaled to span $(-1, 1)$ for numerical stability and ease of notation. The region enclosed by the lower and upper bounds of the variables is termed the design space, the vertices of which determine an m-dimensional cube or hypercube. If each of the variables is specified at only the lower and upper bounds (two levels), the experimental design is called a 2^k full factorial. The second part of the design and analysis of experiments is the statistical analysis. In this stage, the sensitivity of the response to the variables is investigated. The techniques most commonly used are regression analysis and analysis of variance (ANOVA).[3] These techniques are used to perform a systematic decomposition of the variability in the observed response values and to assign portions of the variability either to the effect of an independent variable or to experimental error. The analysis provides information regarding how much each factor (and factor interaction) contributes to the overall variance of the data, indicating the importance (as a percentage) that each factor or interaction plays in the process. These experiments are screening experiments, since the experiments differentiate the important factors and interactions from the unimportant ones. In addition to an ANOVA analysis in the screening experiments, regression analysis can be employed to determine a relationship between the factors and response variables in the form of an equation.[3]

ANOVA allows the testing of the null hypothesis, which states all of the means are equal, against an alternative hypothesis that there is at least one mean that is not equal to the others. The test finds the sample mean and variance for each level of the main factor. Using these values, two different estimates of the population variance are obtained. The first is obtained by finding the sample variance of the n_k sample means from the overall mean. This variance is referred to as the variance between the means. The second estimate of the population variance is found by using a weighted average of the sample variances. This variance is called the variance within the means. Therefore, ANOVA allows us to determine whether a change in the measure of a given variable is caused by a change in the level of a factor or is originated through some random effect. In this way, we can distinguish between the components that cause the variations appearing in a dataset and to determine whether the discrepancies between the means of the factors are greater than would reasonably be expected according to the variations within these factors.

3.1. *Description of problems*

3.1.1. *Mackey–Glass database*

Neuro-fuzzy models were used to predict points of the time series that result from the Mackey–Glass equation integration,[1] given by:

$$\frac{dx}{dt} = -bx(t) + a\frac{x(t-\tau)}{1+x(t-\tau)} \tag{1}$$

This is a time-series with chaotic behavior, recognized as a reference in the study of the learning and generalization capacity of different architectures of neural networks and neuro-fuzzy systems. To obtain the time series value at integer points, a fourth-order Runge–Kutta method was applied to generate 1.000 data points. The time step used assumes the values $x(0) = 1.2$, $\tau = 17$, and $x(t) = 0$ for $t < 0$.

In the statistical experiments, replications were performed using the time-series value in different time steps. Five series w were built, where the objective of the neuro-fuzzy system was to predict future points of the series (y) using past temporal points of the series (x). The series used in the experiments are defined below:

$$\begin{aligned}
w(1) &= [x(t-12)x(t-8)x(t-4)x(t), y(t+4)] \\
w(2) &= [x(t-18)x(t-12)x(t-6)x(t), y(t+6)] \\
w(3) &= [x(t-24)x(t-16)x(t-8)x(t), y(t+8)] \\
w(4) &= [x(t-30)x(t-20)x(t-10)x(t), y(t+10)] \\
w(5) &= [x(t-36)x(t-24)x(t-12)x(t), y(t+12)]
\end{aligned}$$

Offline training was performed using 500 data points ($t = 118$ to 617) by giving four inputs (x) and the attempt was made to predict the output (y). The neuro-fuzzy systems were tested with another 500 data points ($t = 618$ to 1117).

3.1.2. *Gas furnace database*

This is a time-series database for a gas furnace process with gas flow rate $x(t)$ as the furnace input and CO_2 concentration $y(t)$ as the furnace output. This series is the well-known Box and Jenkins gas furnace data.[7] In simulations, we want to extract a dynamic process model to predict $y(t)$ using four candidate inputs to neuro-fuzzy systems. The original data set contains 296 $[x(t), y(t)]$ data pairs.

Replications were performed using the time-series value in different time steps. Five series w were built and are defined below:

$$\begin{aligned}
w(1) &= [y(t-1)y(t-2)x(t-1)x(t-2), y(t)] \\
w(2) &= [y(t-1)y(t-3)x(t-1)x(t-3), y(t)] \\
w(3) &= [y(t-2)y(t-3)x(t-2)x(t-3), y(t)] \\
w(4) &= [y(t-3)y(t-4)x(t-3)x(t-4), y(t)] \\
w(5) &= [y(t-4)y(t-5)x(t-4)x(t-5), y(t)]
\end{aligned}$$

Offline training was performed using the first 145 data points by giving four inputs and the neuro-fuzzy systems were tested with the remaining 145 data points.

3.1.3. *Wine recognition database*

These data are the results of a chemical analysis of wines grown in the same region in Italy, but derived from three different cultivars.[10] The analysis determined the quantities of 13 constituents found in each of the three types of wine. The patterns possess 13 features with three classes defined by the three cultivars.

The database was split into a training and test set. Offline training was performed using the first 133 patterns and the neuro-fuzzy systems were tested with the remaining 45 data points. Replications were performed using five different partitions of the original database. This database was obtained from Ref. 9.

3.1.4. *Iris database*

Fisher's Iris data set contains 150 random samples of flowers from the iris species setosa, versicolor, and virginica collected by Anderson (1953). There are 50 observations for each species regarding sepal length, sepal width, petal length and petal width in centimeters. This data set was obtained from Ref. 9.

Replications were performed using five different partitions of the data. The database was split into a training and test set. Offline training was performed using the first 111 patterns and the neuro-fuzzy systems were tested with the remaining 39 data points.

3.2. *Experiment design*

Design of experiments was applied in order to determine the factors with the greatest influence on the system performance. When analyzing the influence of each of these parameters, the designer should pay close attention to the ones presenting values that are statistically more significant. It should therefore be possible to avoid the necessity for a detailed analysis of different configurations that might, in fact, lead to the design of various neuro-fuzzy systems with very similar behavior patterns.

The response variable used to perform the statistical analysis is the root mean square error (RMSE — between desired and actual output of the system) in the output of the neuro-fuzzy system, when some of the levels of the factor considered vary with respect to a reference design. The changes in the response variable are produced when a new combination of membership function, number of membership functions, training epoch, etc., is considered, thereby changing the design of the neuro-fuzzy system.

In the study performed with ANFIS, we performed a factorial experiment with two levels (2^k factorial experiment), seeking to reduce the amount of experiments run. Table 1 presents the controlled factors. The factors $G = gridpartitions$ (type

Table 1. ANFIS experiment configuration.

	Factors	Levels	
		Inferior (−1)	Superior (+1)
A	Input MF number	2	3
B	Input MF shape	Sine	Triangular
C	Output MF shape	Linear	Constant
D	Training epochs	10	50
E	Initial step size	0.01	0.1
F	Optimization method	Hybrid	Backpropagation

Table 2. EFuNN experiment configuration.

	Factors	Levels	
		Inferior (−1)	Superior (+1)
A	MF number	3	5
B	MF shape	Triangular	Sine
C	Initial sensibility threshold	0.9	0.99
D	Error threshold	0.01	0.16
E	M-of-n	1	3
F	Maximum radius	0.3	0.8

of data partition), $H = 0$ (minimum training error), $I = 0.9$ (increment learning rate) and $J = 1.1$ (decrement learning rate) were fixed during the experiments.

The factors controlled in the design of experiments performed with EFuNN are presented in Table 2. The other EFuNN parameters, $F = 1/\textit{number of samples represented by the node}$ (learning rate for W_1 and W_2), $G = \textit{nonpruning}$ (pruning control) and $H = \textit{nonaggregation}$ (aggregation control) were maintained with default values.

4. Statistical Results

In ANFIS experiments, the analyses were performed in a random fashion. Six control factors (system parameters) were considered — each with two levels — resulting in 64 combinations. Each of the level combinations of the control factors was accomplished five times, totaling 320 analyses.

Through the variance analyses of the factorial experiment, considering the statistical significance level of 5%, four factors were identified in the Mackey–Glass database with a greater influence over the performance of the neuro-diffuse network. Table 3 gives the ANFIS variance analysis of the Mackey–Glass data. The analysis of variance table contains the sum of squares, degrees of freedom, mean square, statistics test and significance level. Note that the output membership function shape adopted and input membership function present the greatest statistical relevance.

The optimization method of training had no influence over the network response. The value of the initial step size also had restricted participation in

Table 3. Mackey–Glass ANFIS ANOVA table.

	S. Squares	D. F	M. Square	F-Ratio	Sig. Level
Main factors					
A	0.0128083	1	0.0128083	282.93	0.000
B	0.0004353	1	0.0004353	9.62	0.002
C	0.0155286	1	0.0155286	343.03	0.000
D	0.0003656	1	0.0003656	8.08	0.005
E	0.0000423	1	0.0000423	0.93	0.335
F	0.0000000	1	0.0000000	0.00	1.000
Significant interactions					
AC	0.0069277	1	0.0069277	153.03	0.000
CD	0.0002206	1	0.0002206	4.87	0.028
DE	0.0002106	1	0.0002106	4.65	0.032

system performance. However, the parameters output membership function shape and input membership function number exercised a considerable influence over ANFIS performance.

The results of this analysis for all databases are displayed in Table 4. For the Mackey–Glass database, the most influential factors were: output membership function shape, corresponding to $\approx 31.72\%$ of the system variance; input membership function number, corresponding to $\approx 26.16\%$ of the variance; output membership function shape, corresponding to $\approx 0.89\%$ of the variance; and training epochs, corresponding to $\approx 0.75\%$.

The interaction between factors (variation among the differences between means for different levels of one factor over different levels of the other factor) was also identified: input membership function number and output membership function shape, corresponding to $\approx 14.15\%$ of the system variance; output membership function shape and training epochs, corresponding to $\approx 0.45\%$ of the variance; and training epochs and initial step size, corresponding to $\approx 0.43\%$ of the total data variance.

In the Gas Furnace database, the most influential ANFIS factors were: output membership function shape, corresponding to $\approx 22.83\%$ of the variance and input membership function number, corresponding to $\approx 20.33\%$ of the variance. The most relevant interaction was between input membership function number and output membership function shape, corresponding to $\approx 14.65\%$. Figure 3 presents the main effects of each controlled factor in the design experiment. The point is that some factors have similar behavior and therefore may exercise no essential influence over the system performance.

For the Fisher Iris data set, the most influential factors were also input membership function number — corresponding to $\approx 13.52\%$ of the variance — and output membership function shape — corresponding to $\approx 8.63\%$ of the variance. The most relevant interactions were among input membership function number, output membership function shape, training epoch and initial step size. Input membership

Table 4. Influence factors analyses.

System	Mackey–Glass Factors	Mackey–Glass Inf. (%)	Gas Furnace Factors	Gas Furnace Inf. (%)	Iris Factors	Iris Inf. (%)	Wine Factors	Wine Inf. (%)	Similar
				Main factors					
ANFIS	B	31.7187	C	22.8338	A	13.5263	A	15.6013	A
	A	26.1622	A	20.3387	C	8.6340	C	6.3340	C
	E	0.8891					B	3.7187	B
	D	0.4506							
	C	0.43012							
				Significant interactions					
	AC	14.1505	AC	14.6532	ACE	3.4871	ACE	5.2871	BE
	CD	0.45	ACE	0.9078	ACD	3.0151	BE	3.7859	ACE
	DE	0.43	AE	0.8187	BE	1.7859	ACD	3.5151	ACD
			ACD	0.6002	BD	1.6746	AB	1.1605	AB
					CE	1.2558			
					AD	1.2087			
					DE	1.1853			
					CDE	0.9616			
				Main factors					
EFUNN	B	68.8400	B	58.4861	B	76.4700	B	66.1116	B
	A	13.1100	E	4.0053	A	0.3900	A	5.5087	A
	E	0.9200	A	0.5647	E	10.1200	D	0.7804	E
	D	0.5400					E	0.2111	D
	C	0.5300							
				Significant interactions					
	AB	12.9200	AB	10.2400	AB	10.2400	AB	12.3352	AB
	BE	0.9000	BE	0.3900	BE	0.3900	BD	0.7804	BE
	CD	0.4800	AE	0.0100			BDE	0.7239	BD
	BC	0.2500	ABE	0.0001			DE	0.7239	AE
	BD	0.2400					ABE	0.4700	ABE
	BCD	0.2300					ADE	0.3681	DE
	AE	0.0500					ABDE	0.3681	ABDE
	ABE	0.0500					BE	0.3644	AE
	CDE	0.0100					AD	0.3296	
	DE	0.0100					ABD	0.3296	
	ABDE	0.0100					AE	0.2612	

function number — corresponding to ≈ 15.60% of the variance — input membership function shape — corresponding to ≈ 6.33% of the variance — and output membership function shape — corresponding to ≈ 3.71% of the variance — was the most influent factors for the Wine Recognition database. In this database, the most relevant interactions among the factors were similar to the others databases.

Figure 4 presents a representation of the interaction between the ANFIS and EFuNN factors in Fisher Iris database. The experiment analyses exposed very similar interactions between the same factors in all databases. A deeper analysis reveals that a statistically larger number of training epochs can aid model generalization. Among the output membership functions, the linear function produces a better

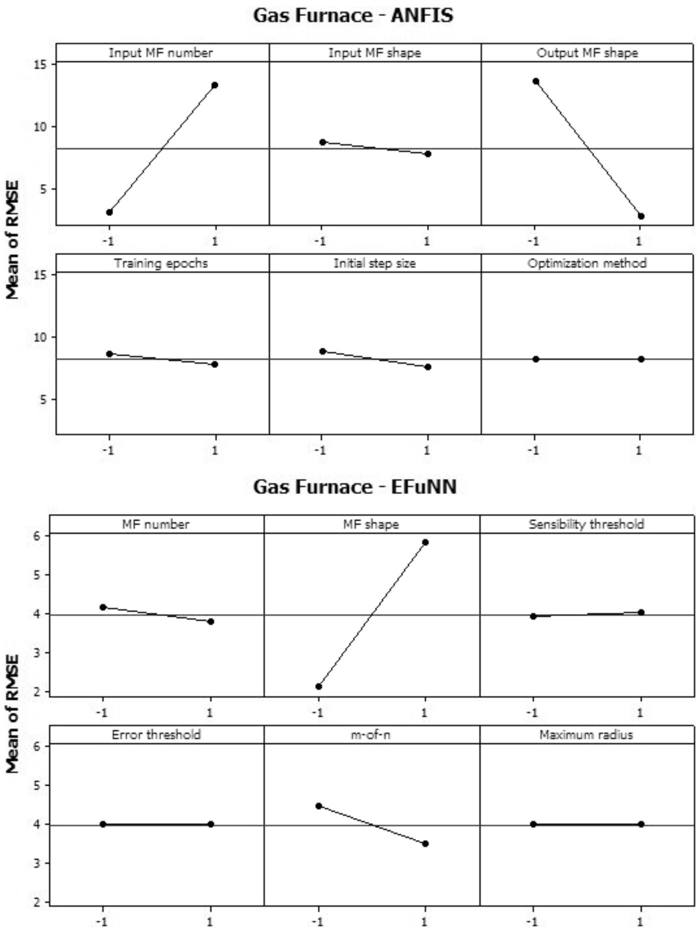

Fig. 3. Main effects projection.

effect on the error surface in the same way as a larger number of input membership functions. The shape of input membership functions had little influence over model variability.

In EFuNN experiments, analyses were performed in a random fashion. Six control factors were considered — each with two levels — resulting in 64 combinations. Each of the level combinations of the control factors was performed five times, totaling 320 analyses.

In the factorial experiment with the Mackey–Glass database, five factors were identified with a larger influence over EFuNN performance (Table 4): membership function shape, corresponding to $\approx$ 68.84% of the system variance; membership function number, corresponding to $\approx$ 13.11% of the variance; m-of-n, corresponding to $\approx$ 0.92% of the variance; error threshold, corresponding to $\approx$ 0.54% of variance; and initial sensibility threshold, corresponding to $\approx$ 0.53% of total variance. The

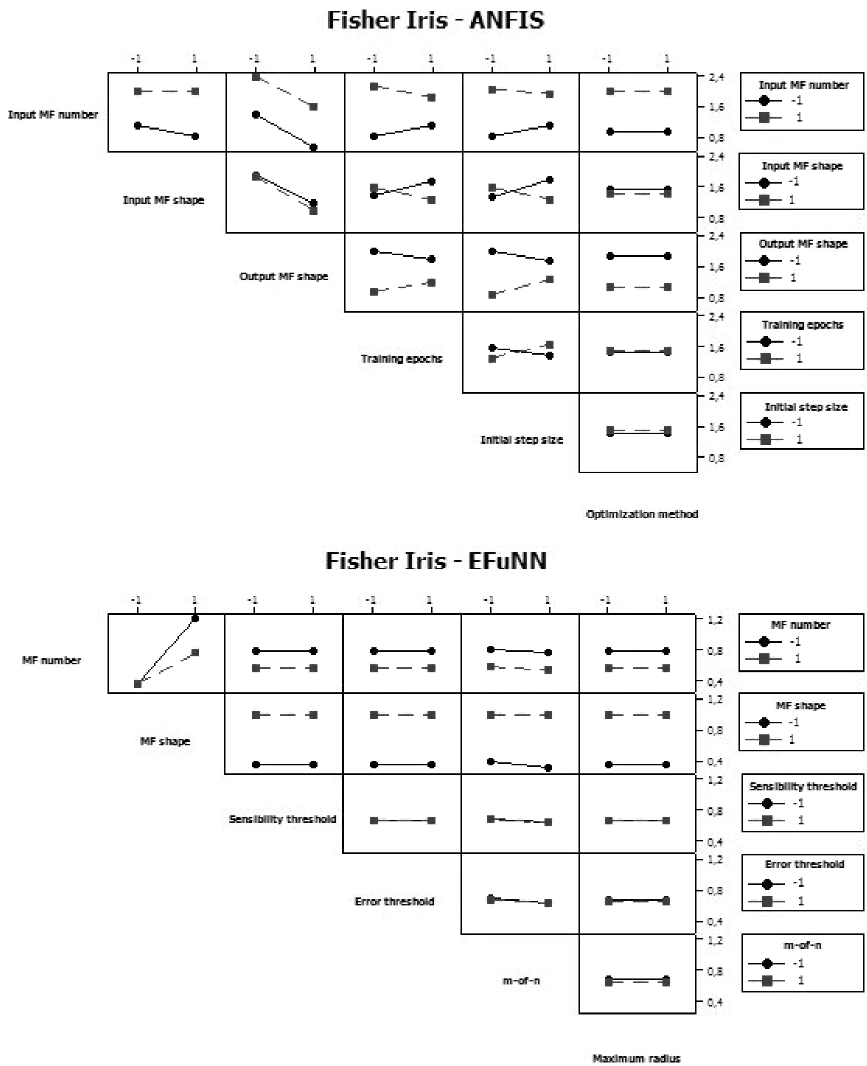

Fig. 4. Interaction projection.

interaction between factors was also identified: membership function number and membership function shape, corresponding to ≈ 12.92% of total system variance; membership function shape and m-of-n, corresponding ≈ 0.90% of total variance; and initial sensibility threshold and error threshold, corresponding ≈ 0.48% of the variance. There were other interactions between factors, but all had a variance smaller than ≈ 0.50% of the total variance of the system.

Figure 5 presents a representation of the relevant factor effects in all investigated databases. The most relevant factors in the four data sets have some similarities. For the Gas Furnace database, the most influent factors were membership function

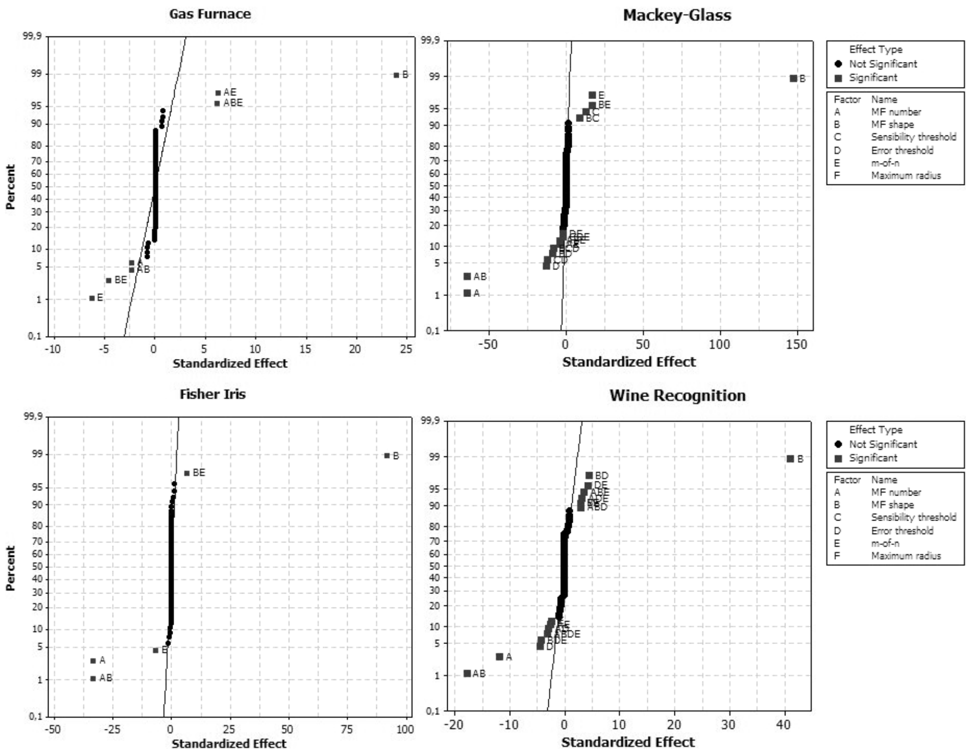

Fig. 5. EFuNN factor effects projection.

shape, corresponding to $\approx 76.47\%$ of the system variance; m-of-n, corresponding to $\approx 0.39\%$ of the variance; and membership function number, corresponding to $\approx 10.12\%$ of the variance. The most relevant interaction was between membership function number and membership function shape, corresponding to $\approx 10.24\%$ of total system variance.

For the Fisher Iris database, membership function shape — with variance of $\approx 76.47\%$; membership function number — with variance of $\approx 10.12\%$; and m-of-n — with variance of $\approx 0.39\%$ — had greater relevance. The interaction between the factor had similar behavior, where membership function number and membership function shape — corresponding to $\approx 10.24\%$ of the system variance — had the most influential interaction. In Wine recognition database, the most influential factors were: membership function shape — corresponding to $\approx 66.11\%$ of the system variance; membership function number — corresponding to $\approx 5.50\%$ of the variance; error threshold — corresponding to $\approx 0.78\%$ of variance; and m-of-n — corresponding to $\approx 0.21\%$ of the variance. The most relevant interaction was between the membership function number and membership function shape.

The membership function shape has the greatest influence over the performance of the neuro-fuzzy model, possibly because it directly influences problem representation. In the experiments, this influence was larger than the influence presented by the addition of new membership functions. However, the interaction between these factors can result in more adapted models.

In the neuro fuzzy system EFuNN, maximum radius, initial sensibility threshold and error threshold are all parameters used to determine if a new node will be created, but they have different influences in the training. In variance analyses, the maximum radius parameter has a small influence over the EFuNN performance. If the sensibility threshold is large, the radius (radius = 1 — sensibility threshold) is very small and it is difficult to violate the area of maximum radius. Maximum radius probably only exercises influence over the results if small values are used in comparison with the sensibility threshold.

The initial sensibility threshold and error threshold have greater participation in EFuNN performance than maximum radius. Although the sensibility threshold is adjusted during training, its initial value exercises a considerable influence in the training. The value of m-of-n also has little influence, though it does exercise a larger influence than maximum radius. This is perhaps characterized by the problem characteristics.

The most important interaction is between the factors membership function number and membership function shape. A low number of membership functions associated to a triangular membership function can result in models with better generalization. The interaction between the other factors was statistically important, but with little representation of the system variance.

5. Final Remarks

This paper presents a study of the different parameters involved in the design of neuro-fuzzy models. The design of experiments was used to analyze and compare experiments by describing the statistical interactions and interrelations between neuro-fuzzy model parameters.

Experiments were performed with four prediction and classification problems. Analyses of the results indicate that the most relevant parameters (over 10% of the system variance) are very similar in the systems for all databases. Another important conclusion regards the interaction of these parameters, which was very homogeneous in each neuro fuzzy system for all databases.

This methodology can reduce efforts in designing neuro-fuzzy systems, reducing both the search space and complexity of the system tuning. In automatic optimization techniques, this information can be mapped in the cost functions for adaptability to consider the optimization of parameters with greatest influence over the neuro-fuzzy system performance. Future work should perform this methodology analysis on other neuro-fuzzy systems and integrate these conclusions to an automated training methodology.

Acknowledgments

The authors would like to thank CNPq and CAPES (Brazilian research agencies) for their financial support.

References

1. M. C. Mackey and L. Glass, Oscillation and chaos in physiological control systems, *Science* **197** (1977) 287–289.
2. N. Kasabov, Q. Song and I. Nishikawa, Evolutionary computation for dynamic parameter optimisation of evolving connectionist systems for on-line prediction of time series with changing dynamics, *Proc. Int. Conf. on Neural Information Processing*, Vol. 1 (2003), pp. 438–443.
3. D. C. Montgomery, *Design and Analysis of Experiments*, 5th ed. (John Wiley and Sons, New York, 2001).
4. J. S. Jang, ANFIS: Adaptive-network-based fuzzy inference system, *IEEE Trans. Syst. Man Cybernet.* **23**(3) (1993) 665–685.
5. N. Kasabov, Evolving fuzzy neural networks for supervised/unsupervised on-Line, knowledge-based learning, *IEEE Trans. Syst. Man Cybernet.* **31**(6) (2001) 902–918.
6. A. Abraham, Neuro fuzzy systems: Sate-of-the-art modeling techniques, *Proc. Int. Work-Conf. on Artificial and Natural Neural Networks* (2001), pp. 269–276.
7. G. Box and G. Jenkins, *Time Series Analysis, Forcasting and Control* (Holden Day, San Francisco, 1970), pp. 532–533.
8. E. Anderson, The irises of the Gasp Peninsula, *Bull. Am. Iris Soc.* **59** (1953) 2–5.
9. C. L. Blake and C. J. Merz, UCI repository of machine learning databases, Department of Information and Computer Science, University of California, Irvine, CA (1998).
10. M. Forina *et al.*, PARVUS — An extendible package for data exploration, classification and correlation, Institute of Pharmaceutical and Food Analysis and Technologies, Via Brigata Salerno, Genova, Italy (1991).
11. G. Franceschini and S. Macchietto, Model-based design of experiments for parameter precision: State of the art, *Chem. Eng. Sci.* **63**(19) (2008) 4846–4872.
12. C. Pierlot, L. Pawlowski, M. Bigan and P. Chagnon, Design of experiments in thermal spraying: A review, *Surface Coatings Technol.* **202**(18) (2007) 532–533.
13. Y. Farzaneh and A. A. Tootoonchi, A novel data reduction method for Takagi–Sugeno fuzzy system design based on statistical design of experiment, *Appl. Soft Comput.* **9**(4) (2009) 1367–1376.
14. C. Zanchettin, F. L. Minku and T. B. Ludermir, Design of experiments in neuro-fuzzy systems, *Proc. V Hybrid Intelligent Systems* (2005).