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Optimal Neuro-Fuzzy model configuration

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Abstract — **The paper is aimed to present how Neuro-Fuzzy Systems can be applied for identifying a general system model of a given problem defined by a set of variables. Neuro-Fuzzy Systems are favored in many application fields because they provide fair accuracy and their inner computational model can be interpreted through the fuzzy rules they encapsulate. The proposed input-output search algorithm is able to find optimal system configuration of an arbitrary set of variables. By placing the algorithm on a Neuro-Fuzzy basis the resulted system model became more interpretable through the inner rules of the Neuro-Fuzzy model. This makes the algorithm more interpretable by revealing more information about the inner connections between the variables of a specific problem.**

I. INTRODUCTION

Neuro-Fuzzy Systems have many applications in various fields such as production, control systems, diagnostic, supervision, etc. [1][2]. They evolved and improved throughout the years to adapt arising needs and technological advancements. Neuro-Fuzzy Systems are hybrid models that utilize the advantages of fuzzy rule systems and ANNs (Artificial Neural Networks): they have learning and generalization capabilities and at the same time they reveal the functionality stored in the model. These combined features make this type of systems useful when solving complex problems.

The paper introduces an algorithm for building up the general system model using Neuro-Fuzzy Systems. System models are extremely important in control solutions e.g. in production control systems, too. Reliable process models are also extremely important in different fields of computer integrated manufacturing. Difficulties in modeling manufacturing processes are manifold: the great number of different machining operations, multidimensional, nonlinear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data, etc. [3][4].

The paper contains five sections. After the introduction the second section presents Neuro-Fuzzy applications and its most common model structure. The third section describes the generalized input-output search algorithm followed by the forth one reviewing the test results and experiences. The last three sections are conclusions, acknowledgments and references.

II. NEURO-FUZZY SYSTEMS

The section discusses some applications of Neuro-Fuzzy Systems and the most important architectures in the field [1][5].

A. *Neuro-Fuzzy Applications*

As it was emphasized already reliable process models are extremely important in different fields of computer integrated manufacturing, especial in system modelling using cybernetics supported solutions [6][7]. Zhang and Morris used a Neuro-Fuzzy solution for fault diagnosis of continuous stirred tank reactor process [8]. They achieved better performance than with a conventional MLP (Multi-Layer Perceptron) while the system also provided a more interpretable structure.

Detecting the onset of damage in gear systems was the goal of Wang et al., for which they developed a neuro-fuzzy based diagnostic system [9]. They also developed a constrained-gradient-reliability algorithm to train the system and their solution outperformed other Fuzzy and Neuro-Fuzzy Systems.

Evsukoff and Gentil created a recurrent Neuro-Fuzzy system for fault detection and isolation in nuclear reactors [10]. In their model a fuzzification module is linked to a neural network based inference module which was adapted to recognize related faults based on the process variables.

One of the first and probably most widespread Neuro-Fuzzy architecture is the ANFIS (Adaptive-Network-based Fuzzy Inference System) which has similar accuracy as the MLP which makes it ideal for function approximation. This architecture was used for mechanical fault diagnostics of induction motors with variable speed drives by Sadeghian and Wu [11]. The authors managed to significantly reduce the system complexity and learning duration of the network by using multiple ANFIS units in their model. In another application Lei et al. used multiple ANFIS combination with genetic algorithm for fault diagnostics of rotating machinery [12].

Machinery malfunctions often reduce productivity and increase maintenance costs in various industrial fields. Zio and Gole proposed a neuro-fuzzy approach to solve fault diagnostic problems by pattern classification while obtaining a model which remained easily interpretable [13]. Chen, Roberts and Weston used Neuro-Fuzzy Systems for fault detection and diagnostics of railway track circuits [14].

Different application fields are also targeted by Neuro-Fuzzy solutions as in the case of another ANFIS model which was used to detect alterations in sleep EEG activity during hypopnoea episodes by Übeyli et al. [15]. The authors used the ANFIS for classification and they performed feature extraction by computing of wavelet coefficients. In their case four models was used: three were fed directly by measured data on the electrodes and the fourth had the purpose of improving diagnostic accuracy by gaining its inputs from the outputs of the other three systems. There is a wide variety of other applications where this kind of systems was successfully implemented from the fields of biology and environment to fault detection and diagnostics as by Kar et al. [16].

B. Neuro-Fuzzy model structure and konwledge interpretation

There are two fuzzy inference types that create the base of the different Neuro-Fuzzy structures; this paragraph explains how to interpret their incorporated knowledge. These are the Takagi-Sugeno-type [17] and the Mamdani-type. The first one is described by rules in the form of

IF $A \in X1$ **AND** $B \in X2$ **THEN** $C = ax_1+bx_2+c$

while the latter one is described by rules in the form of

IF $A \in X1$ **AND** $B \in X2$ **THEN** $C \in X3$

where A and B are the inputs and C is the output; X1, X2 and X3 are fuzzy sets; a, b and c are constants. From the forms of the inference rules it can be seen that the Mamdani-type rules produce fuzzy outputs, while the Takagi-Sugeno type rules produce exact values as a result of a linear equation.

One of the first Neuro-Fuzzy Systems was introduced by Jang [18][19]. This architecture is called ANFIS and it uses the Takagi-Sugeno inference system.

Fig. 1 shows the ANFIS structure which combines the nonlinear membership functions of the inputs with the linear membership functions of the output.

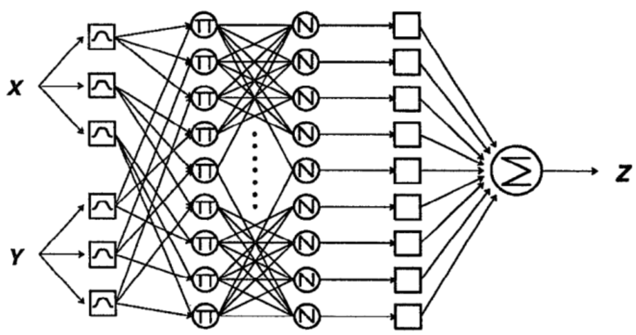


Figure 1. ANFIS architecture [18]

The ANFIS model has the advantage to be the most accurate among the different Neuro-Fuzzy architectures, but it's drawback is that the output membership functions are harder to interpret than in the case of a Mamdani-type inference system.

In the case of the Takagi-Sugeno inference the rules consist of nonlinear antecedent part and linear consequent part.

Fig. 2 shows the input membership functions for one input in the case of two rules. If the membership functions of a given input variable are well separated from each other at the end of the model training it indicates that the connection between the given input variable and the output is nonlinear because different rule is activated in the case of a lower input value than in the case of a higher. For each rule there is a linear output membership function which is weighted with the firing strength of the corresponding rule.

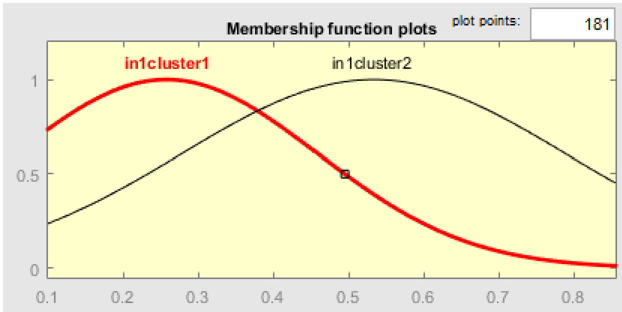


Figure 2. Input membership functions

Fig. 3 shows the coefficients in the output membership function for the two rules. If the input membership functions are well separated then only one rule will fire for a given input vector and only the corresponding output membership function will contribute to the final output value, consequently, linear relationship is applied in the given region.

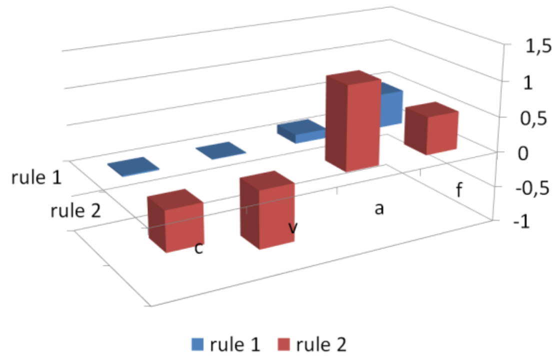


Figure 3. Output membership function coefficients

When the input membership functions totally overlap it means that the input has a linear connection with the output because for any input value both rules fire with similar strength which means both output membership functions are weighted equally and the coefficients are summed respectively resulting in a merged membership function.

These experiences and paper contributions resulted in a methodology to look into and understand deeply the meaning of the individual resulted fuzzy rules (and the related coefficients) also when the system is a Takagi-Sugeno Neuro-Fuzzy but not Mamdani type. Moreover this type of models is more accurate than the Mamdani systems.

One disadvantage of the classic ANFIS structure is that it is only capable to estimate one output value. This problem can be avoided by using the MANFIS (Multi output ANFIS) or the CANFIS (Coactive Neuro-Fuzzy Inference System) [20] model. The former one uses different ANFIS models for each output while the latter one generalizes the ANFIS model to be capable of handling multiple outputs with one model.

III. INPUT-OUTPUT SEARCH ALGORITHM

The solution for identifying a general system model formulated as an input-output search algorithm based on artificial neural networks was developed [21]. By building up of this general model the algorithm does not have any regard to the given assignment of engineers or other experts/users, its target is to satisfy accuracy requirements and build up the most useful system model, e.g. for generalized control aspects. In other words its aim is to build up a general system model pursuing “only” the maximal knowledge identification and incorporation. In this aspect the solution gives up considering the ordering of system parameters to inputs and outputs, its target is to find also the “best” system configuration that maximizes the incorporated knowledge.

Fig. 4 shows the pseudocode of this input-output search where E is a set of error and model index pairs. The model method returns the error of a given model configuration and the min_e and min_i methods return the error and index of the element of E respectively where the error is minimal.

```
iosearch(el, P)
    I <- P
    O <- Ø
    em <- ∞
    WHILE |I| > 1 AND em < el
        E <- Ø
        FOREACH i IN I
            e <- model(I \ i, O U i)
            E <- E U (e, i)
        END
        em <- min_e(E)
        p <- min_i(E)
        I <- I \ p
        O <- O U p
    END
END
```

Figure 4. Pseudocode of the input-output search

In this generalized algorithm the model method can be implemented as the evaluation of an arbitrary (forward) computational model like ANN or a Neuro-Fuzzy System. This algorithm was generalized earlier to use SVM (Support Vector Machine) models, too [24].

IV. Test Results and Experiences

This section details the test results of the input-output search on different test cases and the interpretation of the optimal models.

A. *Test cases*

Four datasets were used for evaluation of the general model search algorithm; these test cases were selected to cover a wide variety of problem types.

The first dataset is from the field of cutting theory, applied typically cutting tool machining companies and their customers. 9 variables consist of machine settings, like feed and speed, and measurable process variables like force and roughness [3].

$$\begin{aligned} F_c &= 1560 \cdot f^{0.76} \cdot a^{0.98} \cdot (\sin(\chi))^{-0.22} \\ P &= 0.039 \cdot f^{0.79} \cdot a \cdot v \\ T &= 1.85 \cdot 10^{10} \cdot f^{-0.7} \cdot a^{-0.42} \cdot v^{-3.85} \\ R_a &= 8.5 \cdot f^{1.8} \cdot a^{0.08} \cdot v^{-0.9} \cdot r_\varepsilon^{-0.5} \end{aligned} \quad (1)$$

In this case the dependencies are described by special equations and values for the related variables are generated by four equations (1) which were defined by cutting tool manufacturers.

The second test case is also from cutting process, but in this case the dataset contains measured values of 7 variables [21]. This dataset represents the real production environment where the values can contain noise and the measurement system is not fully ideal.

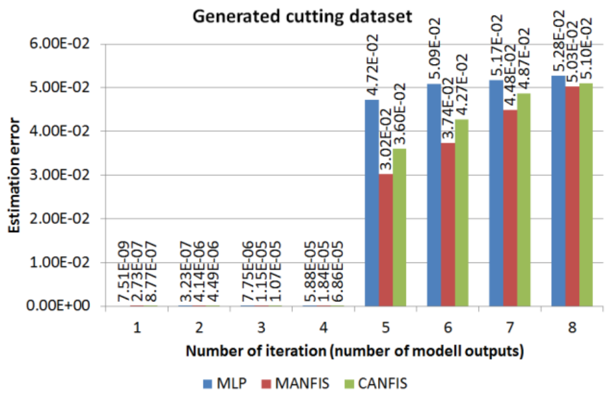
The third test case is the well-known Iris dataset from UCI Machine Learning repository [22]. This dataset contains 4 geometrical variables (sepal and petal length and width) and one classification variable with three different class values (three types of Iris flower).

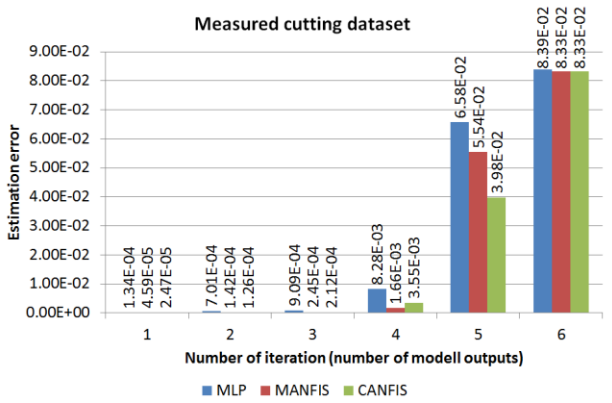
Finally, the fourth test case, another dataset from UCI Machine Learning repository [22], is housing which consists of 14 variables describing real estate properties in the outskirts of Boston.

B. *Optimal Models*

The input-output search was applied on each test dataset without defining an error limit thus forcing the algorithm to run until all the variables except one are put on the output side of the model Modell estimation error was used to measure the accuracy of possible model configurations considering different amount of model output variables.

Fig. 5 shows the search results on the 4 datasets comparing the MLP, MANFIS and CANFIS models. The diagrams show how the estimation errors of the models grow as more and more variables are placed on the output side (consequently, less and less variables remain on the input side). Moreover, it is represented that Neuro-Fuzzy models are more accurate than the MLP model types.





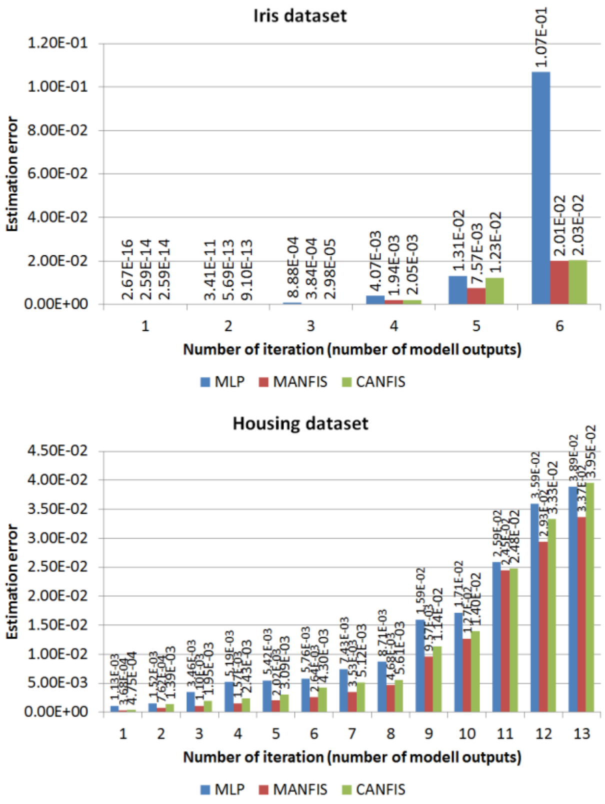


Figure 5. Error of various input-output search results for different model output variable amounts.

One can see that typically there is a drastic leap in the error at a specific output number. For example in the case of the calculated cutting dataset the 4 output model has a fairly low error but the 5 output model has very poor accuracy. This is due to the fact that the dataset was generated from 4 equations. It can be noticed that because this dataset was generated by using the equations in (1), the problem can be estimated with high model accuracy.

In the case of the three other datasets the data comes from measurements, which typically incorporate noise in the values and the connections of the variables are also more uncertain. The measured cutting datasets shows a leap in the error between the 4 and 5 output model. The Iris dataset produces similar accuracy at 3 and 4 output which is due to the fact that the original 4 geometrical variables (Sepal length, Sepal width, Petal length, Petal width) are redundant and the input-output search puts one of these variables (the first one) to the output side. The Housing dataset is the hardest to estimate which can be seen from the relatively high error values. In this case there isn't a definitive leap in the error and the 5-6-7-8 output models can all be considered as optimal system model.

C. *Interpretation of the resulted optimal model using the Iris dataset as example*

In the case of Iris that has the highest ranking among machine learning benchmark datasets [22], both the 3 and 4 output models have similar accuracy making them both valid system models. The 3 output model is the direct model because the 4 inputs are the geometrical variables while the 3 outputs are the classification values of the three classes (for classification problems the class variable is often partitioned into 0-1 type variables for each class and the model diagnosis is the one variable that is the closest to 1).

Fig. 6 shows the membership functions of the 4 geometrical input variables (from top to bottom respectively) for identifying the first class (in this case the MANFIS model is used so there is a different ANFIS model for each output). It is represented again, that Neuro-Fuzzy systems can serve with more accurate models than pure MLP solutions that is a general experience after the tests.

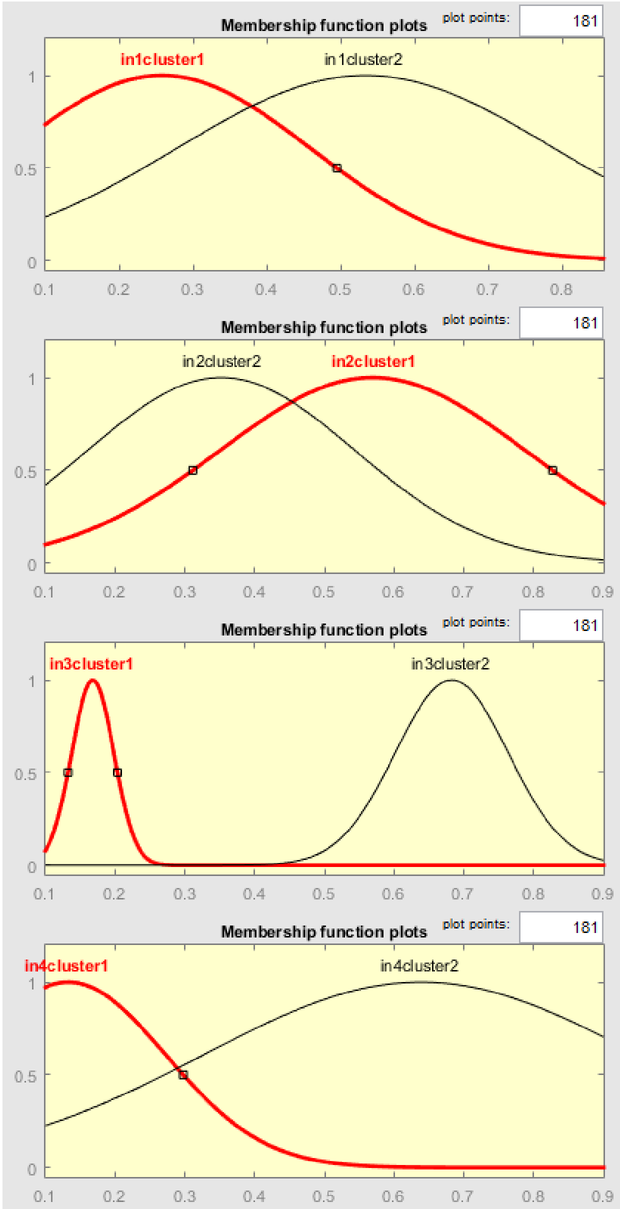


Figure 6. Input membership function of the 3 output model (first class output)

Fig. 7 shows the membership functions of the Sepal width, Petal length and Petal width input variables (from top to bottom respectively) for identifying the first class as the input-output search put the Sepal length variable to the output side.

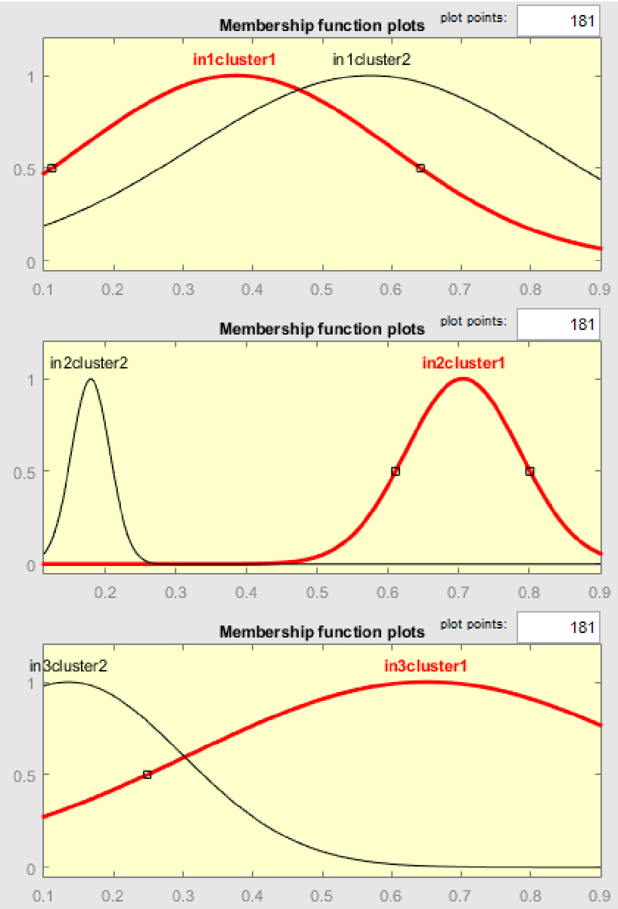


Figure 7. Input membership function of the 4 output model (first class output)

It represents that the corresponding membership functions are basically the same for both models with four and with three input variables, which also means that *input-output search identified that the first class can be diagnosed based only on these 3 inputs*. The same conclusions can be drawn in the case of the other two classes which means that *the input-output search successfully identified a redundant variable* and put it on the output side.

So the 3 class variables can be estimated form 3 geometrical variables but it is also expected of the model to give good estimation for the identified output geometrical variable. Fig. 8 shows the membership functions of the Sepal width, Petal length and Petal width input variables (from top to bottom respectively) for estimating the geometrical output variable Sepal length.

It is represented in the Fig. 8. that the relative location of the membership functions can be interpreted as that the Petal length input has the most impact on the Sepal length (as it is the most separated) and the Sepal width input has the least impact (as it is the most overlapping).

Fig. 9 shows how the three classes are located in the space of different geometrical variable pairs. It can be seen that the location of the classes completely correspond the membership function overlap of Fig. 8.

This behavior of the membership functions mirrors that it is possible to interpret also the ANFIS based Neuro-Fuzzy rules, moreover the introduced algorithm for determining Neuro-Fuzzy model configuration is able to result in the optimal system mapping.

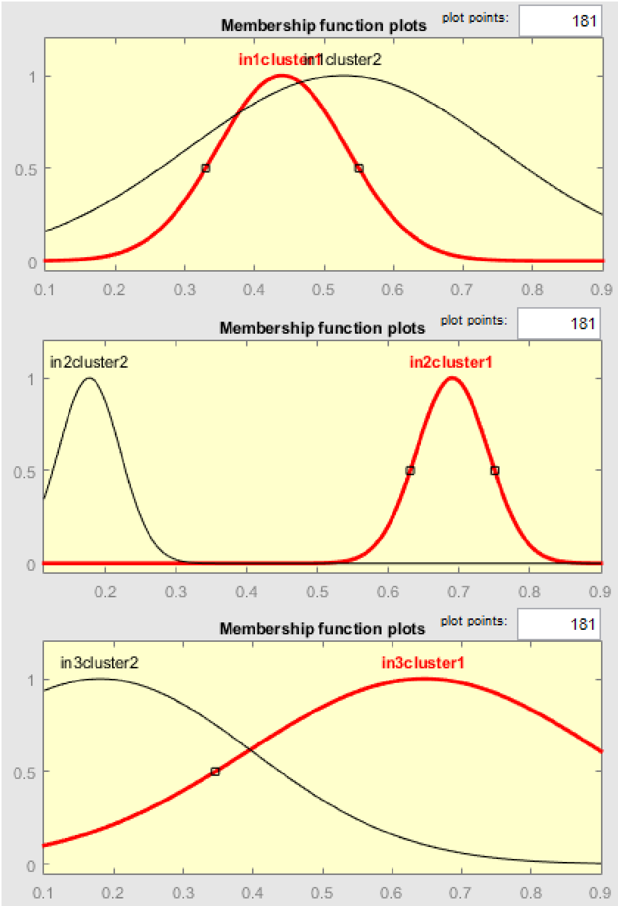
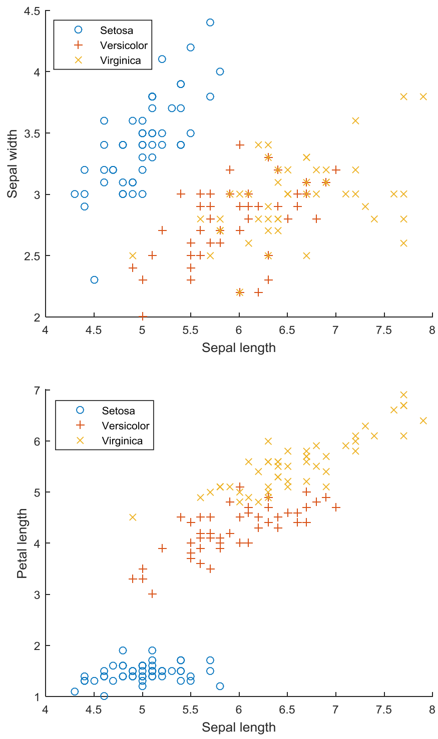


Figure 8. Input membership function of the 4 output model (geometrical output)



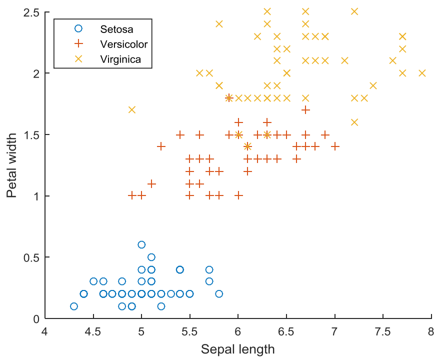


Figure 9. Location of the three classes in the space of the geometrical values

V. CONCLUSION

This paper presented how Neuro-Fuzzy Systems can be used for identifying general system models of a given problem defined by a set of variables. Neuro-Fuzzy Systems are favored in many application fields because they provide high accuracy and their inner computational model can be interpreted through the fuzzy rules they encapsulate. The input-output search algorithm is able to find optimal system configuration of an arbitrary set of variables. By placing the algorithm on a Neuro-Fuzzy basis the resulted system models became more interpretable through the inner rules of the Neuro-Fuzzy model. This makes the algorithm more efficient by revealing more information about the inner connections between the variables of a specific problem that can be exploited later in many applications [23].Furthermore the input-output search was integrated into the submodel search algorithm which is able to identify variable subsets which can be modelled with a given accuracy [25].

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