AN HYBRID INTELLIGENT SYSTEM AND MODELS FOR PROTECTING WATER SUPPLY QUALITY USING GIS

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Abstract: The rapid growth in the number and variety of applications of the fuzzy logic controller and neural networks reflects the advantages of the intelligent techniques applications. Neuro-fuzzy modeling is aimed at solving real world decision making, modeling and control system problems, witch are usually imprecisely designed and require human operator intervention. In this paper neuro-fuzzy method with their ability to incorporate human knowledge are used in the conception and design of hybrid intelligent systems and models. Implementation of the neuro-fuzzy models and algorithms by using the weighting sums method is proposed

Keywords: neural network, pollution, GIS, fuzzy, hybrid, water,

1. INTRODUCTION

In the real world computing problems it is advantageous to use two or more computing techniques synergistically rather than exclusively, obtaining in construction of complementary hybrid intelligent systems. In this direction the neuro-fuzzy computing techniques include neural networks that recognize pattern and adapt themselves to cope with changing environments and fuzzy logic inference systems that incorporate human knowledge and accomplishes inference and decision making. The combination of this two complementary approaches, together with other techniques as is genetic algorithms, will result in menu model design method of the control application. The main characteristics of the neuro-fuzzy modeling are soft computing utilizes human expertise in the form of fuzzy if-then rules, artificial neural networks are inspired by biological neural networks, both neural networks and fuzzy inference system exhibit fault tolerance, these methods can be applied for large scale problems which incorporate built-in uncertainties and this methods offer new application domains which are computation intensive

2. NEURO-FUZZY STRUCTURES

The use of the neuro-fuzzy methods represents a way to combine advantages of the fuzzy techniques and neural networks. Neural networks having training properties they can be use to design membership functions, which need a smaller function in real time applications. The most important advantage of the fuzzy systems is the possibility to use in the model design the human operator experience by choose of the rule tables and inference rules. The neural networks allow graphically represent the design steps and choose of the network parameters can be accomplished by precise methods. There are three methods to design neuro-fuzzy models or digital controllers:

1) The use of separated neural networks modules and fuzzy logic modules, which are serially or parallel connected to obtain a control algorithm, figure 1.

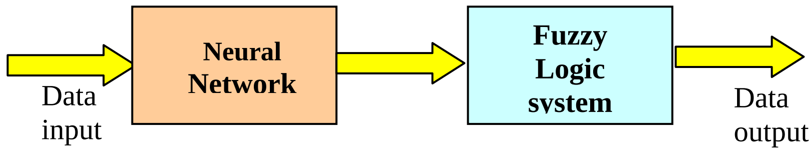

Fig. 1. Connected serial

2) The implementation of the concrete fuzzy logic models function by neural networks. This method can be used, for example, for membership function design, or for data acquisitions modules. This method allows to design digital fuzzy controllers with nonlinear membership functions, witch are implemented by neural networks, fig. 2

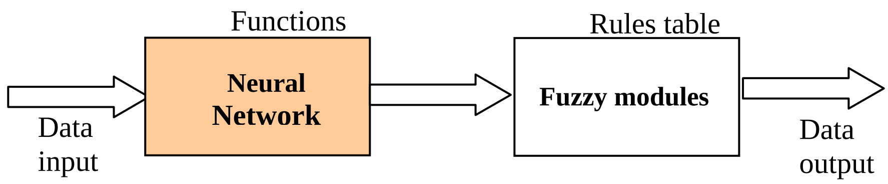

Fig. 2. Design digital fuzzy controllers with nonlinear membership functions, witch are implemented by neural networks

3) The implementation of the fuzzy logic algorithm by using of the neural network structures. By this method all fuzzy controller function are implemented by neural networks, fig.3 .

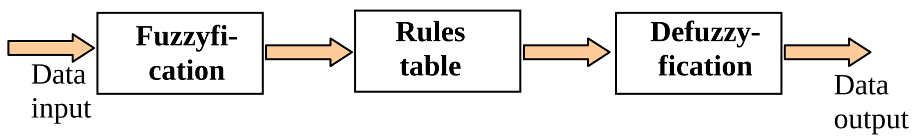

Fig. 3. Implementation of the fuzzy logic algorithm

This method can be separaitly applied for each functions or for global functions of the fuzzy digital controller The neuro-fuzzy methods for digital controller design can be used in the process identification, in the fuzzy digital controller design, in the monitoring system. The symbiosis of the neural networks and fuzzy logic systems in the device design will improve the system performances. In the design of neuro-fuzzy systems some conditions are to be accomplished: complectness of the definitions domain with membership functions for input variables, fuzzyness conditions which imposes to exist a prevailing fuzzy rule for each input signal combinations, and conditions to choose a training methods which will not change the type of the membership functions.

3. PROCEDURES FOR NEURO-FUZZY MODEL DESIGN.

For neuro-fuzzy model design the following three procedures can be used:

- Implementation of neuro-fuzzy systems by using of fuzzy neurons. A fuzzy neuron, fig. 4, is defined by equations:

$$y = \begin{cases} 1 & \text{, if } v \geq \theta_1 \\ g(v) & \text{, if } \theta_1 <= v <= \theta_1 \\ 0 & \text{, if } v < \theta_1 \end{cases}$$

$$\text{where } v = \sum_{i=1}^{n} x_i w_i \tag{1.2}$$

Identically can be defined neurons with different functions: max, min, implication, Cartesian product, etc., which represent units for logic operations. The use of the fuzzy neurons for the implementation of the neuro fuzzy models and algorithms has the advantage that a graphical representation of the all logic and arithmetic operations is obtained, but it has the disadvantage that only for a small number of variables can be used, usually for two or three variables. By this method all operations in a fuzzy controller: fuzzyfications, inference and defuzzyfications can be realized by fuzzy neurons using.

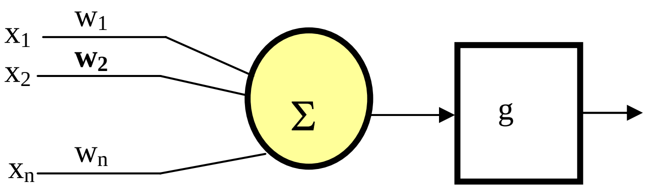

Fig. 4. A fuzzy neuron

- Implementation of the neuro-fuzzy models and algorithms by neural modeling of the fuzzy logic structure. This method can be applied for different method of inference, for example Mamdani, Sugeno, Tsukamoto, etc. For example, for two fuzzy variables x_1 and x_2, and for membership functions A_1, A_2, B_1, B_2 the following equations are used

if x_1 **is** A_1 **and** x_2 **is** B_1, **then** $f_1 = p_1x_1 + q_1x_2 + r_1$

if x_1 **is** A_2 **and** x_2 **is** B_2, **then** $f_2 = p_2x_1 + q_1x_2 + r_2$

where (p_i q_i r_i) are constant parameters which are choused by model designer. The output command value is:

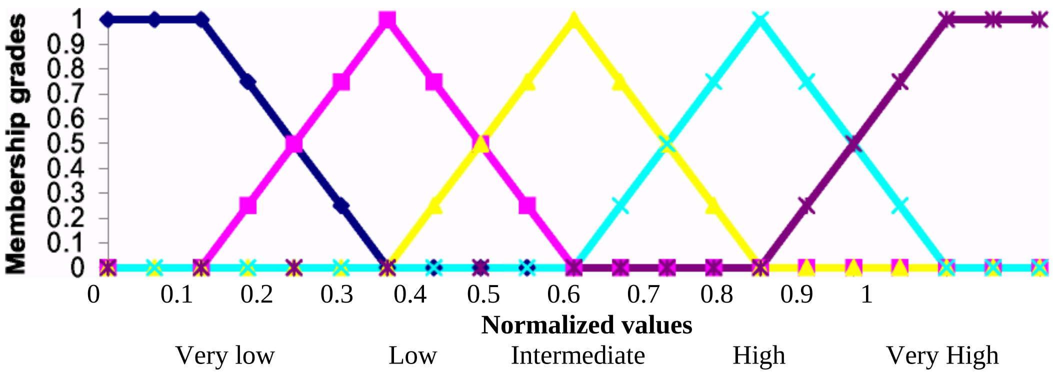

Fig. 5. Membership functions for WATER

$$y = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 =$$

$$= \overline{w_1} f_1 + w_2 f_2$$

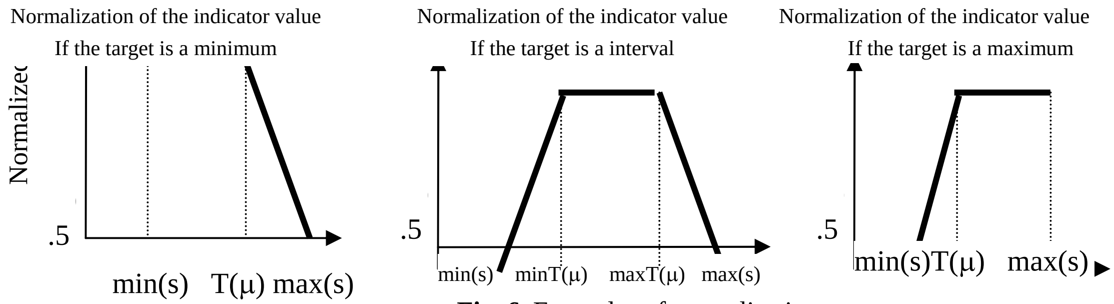

Fig. 6. Examples of normalization

Different curves of normalization can be used according to needs and context. Let μ_i be the data value of indicator i. Then its normalized value N(μ_i) is calculated as follows.

1.	**If** the target value T(μ_i) corresponds to a maximum:	$N(\mu_i) = \begin{cases} \dfrac{\mu_i - \min(s)}{T(\mu_i) - \min(s)} & for \ \mu_i \le T(\mu_i) \\ 1 & for \ \mu_i \ge T(\mu_i) \end{cases}$	**(1.1)**
2.	**If** the target value T(μ_i) corresponds to a minimum:	$N(\mu_i) = \begin{cases} 1 & for \ \mu_i \le T(\mu_i) \\ \dfrac{\max(s) - \mu_i}{\min(s) - T(\mu_i)} & for \ \mu_i \ge T(\mu_i) \end{cases}$	**(1.2)**
3.	**If** T(μ_i) corresponds to an interval [min(T_μ), max(T_μ)]:	$N(\mu_i) = \begin{cases} \dfrac{\mu_i - \min(s)}{\min T(\mu_i) - \min(s)} & for \ \mu_i \le \min T(\mu_i) \\ 1 & for \ \mu_i \in [\min T(\mu_i), \max T(\mu_i)] \\ \dfrac{\max(s) - \mu_i}{\max(s) - \max T(\mu_i)} & for \ \mu_i \ge \max T(\mu_i) \end{cases}$	**(1.3)**
4.	**If** T(μ_i) corresponds to "**Yes**" or "**No**" statements	$N(\mu_i) = \begin{cases} 0.5 & for \ \mu_i = T(\mu_i) \\ 0 & for \ \mu_i \ne T(\mu_i) \end{cases}$	**(1.4)**
5.	Finaly, the value of each linguistic variable is given by the average aggregation:	$N_i = \left\{ \dfrac{\sum_i N(\mu_i)}{n_i} \right\}$ Where: ***T*** = observed values of the linguistic variables WATER*, LAND*, BIOD*, , $\mathbf{n_i}$ = total number of indicators specifying each variables.	**(1.5)**

Instead of using the data for each indicator directly it is need to normalize them to obtain a common scale and allow statistical aggregation. The rationale of normalization of indicator values is illustrated in Figure 5

- Implementation of the neuro-fuzzy models and algorithm by using the weighting sums methods. This proposed method consists in using of the three models M, S and T, fig.5, where two variables are considered and where through y^M, y^S and y^{Ts} are represented the outputs of the Mamdani, Sugeno and Tsukamoto models.

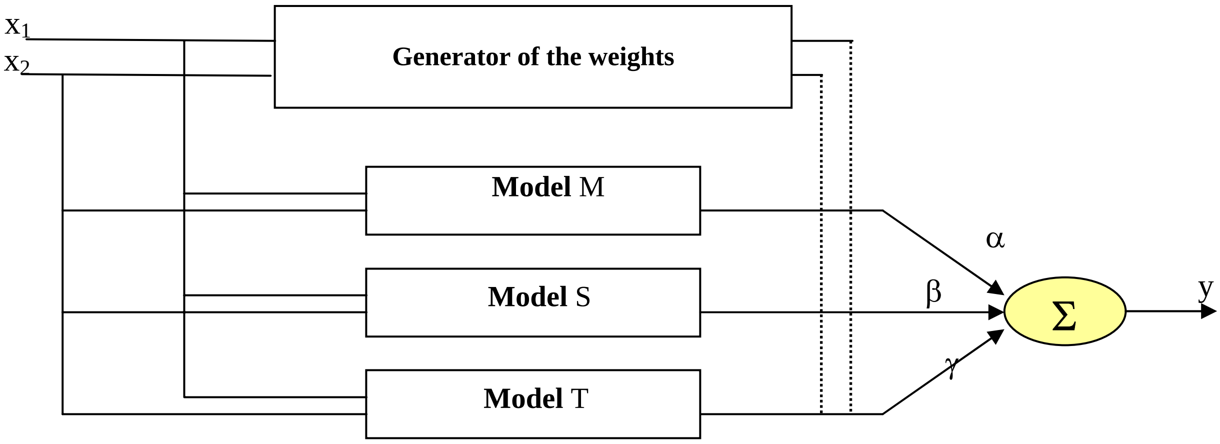

Fig. 7. Using of the three models M, S and T, (Mamdani, Sugeno and Tsukamoto models).

The input of the neuro-fuzzy model is defined by equation

$$y = \alpha y^{M} + \beta y^{S} + \gamma y^{Ts}$$

where α, β, γ are weighting constants which has the restrictions:

$$\alpha + \beta + \gamma = 1$$

The proposed method was simulated for applications with two variables. The obtained results revealed that a better filtration of the human operator error is obtained and a local optimum of the parameters values can be avoided. The motivation for coupling one or more AI methods into a hybrids system is, in general, one of the following [6]:

1) Function-replacing-enhancing one AI method by means of another in order to overcome the limitations of the former;
2) Method intercommunication – when problems with multiple objectives (subproblems) solvable by different methods are encountered;
3) polymorphism – development of polymorphic systems which display properties of different methods within a single architecture.

Hybrid systems can be classified accordingly, on basis of their functionality, processing architecture and communication needs. Hybrid system belonging to the first class are associated with particular methods: a selected AI method is being improved by coupling with another AI method. Enhancement of the basic method usually results either in faster execution or increased reliability The development of a hybrid system usually consists of the following six stages:

a) Problem analysis;
b) Identification of the properties required by an intelligent method in order to solve the given problem, followed by the section of appropriate method(s);
c) Selection of an appropriate hybrid system type;
d) Implementation;
f) Validation;
g) Maintenance.

Hybrid intelligent systems represent not only a combination of different intelligent methods, but also their integration with conventiona computer systems: database applications, spreadsheet applications, GIS environment, etc., with the ability to interchange data with different processes using different media.

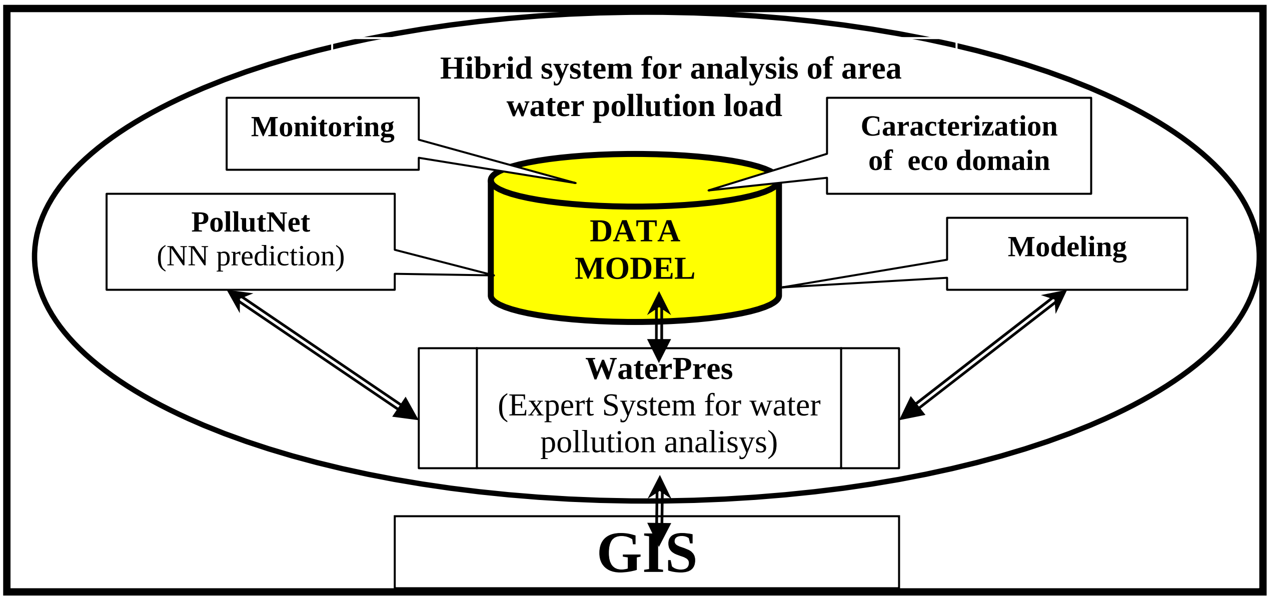

Fig. 8. Hibrid system for analysis of area water pollution load

In order to obtain a general picture of water pollution for a wider area systematic measurements of different pollutants are organized on five measuring locations. These measurements are periodic by their nature and, due to the complexity of the task, are conducted by specialized institutions.

4. CONCLUSIONS.

Neural computing systems are suited to problems whose solution is complex and difficult to specify, but which provide an abundance of data from which a response can be learnt. By virtue of their construction, neural networks are large non-linear processors that can be trained for use in a wide range of real - world situations. The training of the neural network demands a lot of computer power, but the computational requirements of a fully trained neural network when it is used in recall mode can be more modest. The adaptability, developing solution faster, computational efficiency, generalising from examples are the main attributes of the NN.
Structure identifications in neuro-fuzzy modeling involves the selecting relevant input variables determining an initial architecture, including input space partitioning, number of membership functions for each input, number of fuzzy if-then rules and choosing initial parameters for membership functions. The proposed method for neuro-fuzzy system can be used in system identification and in control algorithm design.

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