Decision support tool based on neuro-fuzzy environmental approach

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Abstract. Environmental issues have become more visible and more compelling for the society we live in, which led to increased public interest for better understanding ecosystems in order to intervene and mitigate the human negative impact over environment. The paper aims to present a neuro-fuzzy based system for ecological assessment. The result of the paper consists in determination of appropriate methods of action for reducing adverse effects on environment and implicit the population. It is noted that this subject of research represent a high interest current in the world.

Keywords: assessment tool, neuro-fuzzy, environmental sustainability;

1. Introduction

In our era growing of consumption of natural resources necessary to sustain human activities is one of the factors that led to major climate changes affecting in this way the delicate balance of the environmental systems. Starting from this reality, the increasingly wider society concern for environmental protection has been taken at the highest decision-making forums, becoming a basic principle of both national and international policy. The range of issues which may need to be considered while preparing an environmental assessment is very large indeed. Some become relatively more important at one time than at another, while new problems arise constantly. For this reason, among others, it is difficult to build into legislation or regulations a required set of items to be covered in every case.

This paper presents some currently important contemporary issues, and suggest ways in which consideration of these problems can enter into an assessment. There are certainly many other problem areas that may be more important in certain instances, but each of these has some history of being relevant to national and international decision making [1].

A socio-environmental system cannot be entirely and efficiently described only through simple mathematics rules. Sustainability is difficult to define or measure because it is inherently vague and complex concept [2].

In this paper, a neuro-fuzzy model is presented, which uses data sampled from different parameters in order to assess on environment. If classical mathematical methods cannot provide solutions by representing uncertain data and handling vague situations, one possible solution to represent these conditions can be the use of fuzzy logic. Therefore, a neuro-fuzzy model using as input basic indicators of environmental integrity and neuro-fuzzy reasoning methods to provide sustainability measures was developed. The method can be used as a potential tool for decisions making responsible in order to assets or to predict the environmental impact of their actions.

2. Environmental structure presentation

Worldwide, the regional or county environmental performance assessment is becoming a major issue. Making an integrated analysis of a variety of factors and the existing relationships between these factors, i.e.
assessing the performance of an environmental system, is often a difficult problem. Often, for each indicator, specific types of information are used. Therefore, specific tools and creative approaches are needed.

The architecture of the environmental assessment system proposed in this paper involves three components: a water quality assessment module (WATER), a soil integrity evaluation module (SOIL) and an air quality assessment module (AIR). Fig. 1 illustrates the dependencies of between components for environmental assessment. The environmental assessment is influenced by different parameters, such as air quality impact, water quality or soil integrity. If considering the environment as biodiversity, the set of factors that influence its assessment is complex. However, for the moment, only three factors with a predominant role are analyzed, representing the decision criteria.

Fig. 1: Dependencies of evaluation components

In this paper, the decision criteria are classified into three main categories namely: AIR (air quality), WATER (water quality) and SOIL (soil integrity). In order to create the decision criteria, several other parameters that affect these base criteria are considered, such as evaluation criteria [3].

Each and every one of these parameters is characterized by Pressure (PR), State (ST), and Response (RE) indicators. State is the present state of a component such as the size of forested land. Pressure is a force tending to change State such as the deforestation rate. The response it is about to bring pressure to a level that will ensure a better state, for example, protecting a certain area. Pressure-state-response approach was originally proposed by the Organization for Economic Cooperation and Development (OECD, 1991) to assess the environmental component of sustainability. A detailed review and variants of this approach are presented in Spangenberg and Bonniot (1998).

The indicators used previously and now for modeling are given in Table 1 [4]. Statistical data for these indicators are provided by many sources as United Nations organizations, World Resources Institute, governmental and nongovernmental environmental organizations etc. Definitions of those three environmental components are adopted from IUCN/UNEP/WWF (1991).

In order to apply the methodology for environmental assessment the city of Iasi located in the north-east of Romania, it was chosen. The town area is about 3770 hectares and a population of 340,000. By the mid '90s, the city was an important industrial center in Romania but since then, the economy went down, unfortunately, instead leaving high values of pollution levels (toxic solid and liquid waste).

Table 1. Indicators used for environmental assessment [4]

<table>
<thead>
<tr>
<th>Component</th>
<th>Pressure</th>
<th>Status</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIR</td>
<td>SO₂ emissions, CO₂ emissions, CH₄ emissions</td>
<td>Atmospheric concentration of greenhouse and ozone depleting gases: CO₂, NO₂, SO₂, CH₄, CFC-12</td>
<td>Fossil fuel use, Primary electricity production, Public transportation</td>
</tr>
<tr>
<td>WATER</td>
<td>Water pollution, Urban per capia water use, Freshwater withdrawals</td>
<td>Annual internal renewable water sources</td>
<td>Percent of urban wastewater treated</td>
</tr>
<tr>
<td>SOIL</td>
<td>Solid and liquid waste generation, Population density, Growth rate, Commercial energy use</td>
<td>Net energy imports, Domesticated land, Forest and wood-land area</td>
<td>Primary energy production, Nationally protected area, Urban households with garbage collection</td>
</tr>
</tbody>
</table>

The components of environmental assessment (AIR, WATER, and SOIL) and their various characterizing indicators are presented in Table 1. To be able to evaluate the environment of a particular region, first of all there have to be the possibility to assess it, using different instruments. Without these tools
it is difficult to formulate a coherent strategy. From the more than 68 environmental parameters from database only those were selected which are most important for the decision making process. A number of hard constraints for these attributes have been applied in accordance with environmental policies of which 26 matches’ last constraints that were placed in a new database as can be seen in Table 1 (adapted from [4]) When these indicators change, and their change has impact on assessment, the most important parameters can be identified that help or hinder its progress towards environmental sustainability. As a result, the next step is materialized in recommending actions to increase or decrease the values of the indicators identified as having a role in promoting or hindering sustainable environmental development [5].

3. Environmental approach based on neuro-fuzzy inference system

Fuzzy modeling techniques, namely, the construction of fuzzy rule-based inference systems, can be viewed as grey-box modeling because they allow the modeler to extract and interpret the knowledge contained in the model, as well as to imbue it with a-priori knowledge. However, the construction of fuzzy models of large and complex systems—with a large number of intricately related input and output variables—is a hard task demanding the identification of many parameters [6].

The use of fuzzy membership functions is convenient because it allows the problem to be recognized as it is in real life. All this makes the environmental assessment challenging, yet a crucial task to perform. A lot of organizations have experts who are responsible for this task. Currently, the environmental assessment is performed manually and every technique meant to automate this process can prove invaluable for everybody involved. This paper proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS) which can learn to make human-like decisions and uses fuzzy membership functions to point out satisfaction degrees[7]. Further on, a small number of fuzzy rules has been extracted, which are very effective, without disturbing the robustness of system.

After the system is trained, it can be adapted to environmental changes in order to increase its efficiency. Moreover, using the information provided by experts from time to time, the system may learn to make better and up to date human-like decisions. This system can be easily used by the experts in environment assessment, due to the implementation of the fuzzy membership functions, being able this way to easily express their decisions in terms of linguistic descriptions (such as good, average, low) regarding the constraints.

However, there is another problematic issue because different experts may provide fairly diverse decisions, due to their personal experience, current environmental situation, not to mention mistakes. Moreover if the same data would be presented to the same expert at a different time, it is estimated that 20% difference would occur.

ANFIS uses a hybrid learning algorithm to identify the membership function parameters of single-output, Sugeno type fuzzy inference systems (FIS). A combination of least-squares and back-propagation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data.

Application of a neuro-fuzzy inference system to model real-life problem is quite normal, because of similarity to real human decision making [8]. Some design problems have been established on the basis of human environmental experts, while others were learned and experienced. Some design issues were the following:

• Number of input membership functions: the fuzzy membership functions were set up based on knowledge on expert decisions. Three membership functions have been determined (low, average and high) for each of three soft constraints model (AIR, WATER, SOIL)

• Type of input membership functions: based on the properties of the constraints, triangular membership functions are considered.

• Type of output membership functions: the system uses a single output, obtained using weighted average defuzzification. All output membership function had the same type and were either constant or linear [9].

• The number of output membership functions: it ranged from 2 to 81.
• The number of rules: for a well defined fuzzy system, control actions need to be defined (fuzzy output) for every possible combination of input membership function values. In this case, three constraints, each with three membership functions result in $3^3 (27)$ fuzzy rules, where the linguistic values were not negated, and they were connected with “and” relation.

• Performance function: some of the widely used performance functions in neural networks are Sum of Squared Error, Mean Squared Error, and the following cost function (Eq. 1) [10]:

$$J = SSE + \lambda \sum |w|$$  

where: SSE is Sum of Squared Error; $\lambda$ is a penalty factor; and $w$ is weight;

• Optimization methods: back-propagation and hybrid (mixed least squares and back-propagation ) methods had been used as optimization methods.

• The data was split into training, cross-validation and testing sets. The range of the training data set size is between 50% and 90%. The cross-validation and testing data sets each will take half of the rest of the data (5%-25%). The use of cross-validation is optional but in this implementation is important, to avoid overtraining.

• Number of epochs: there is the belief that 400 are good enough for a good network performance.

Through an adaptive neuro-fuzzy inference system the range of the membership functions are learned, fuzzy rules are created and their weights are adjusted in order to better model the training data. The performance function values are calculated, and classification is provided [11].

4. Results and discussion

The presented methodology was implemented in the Matlab programming language environment with the fuzzy logic toolbox [9]. From the multitude of tested membership functions, the triangular membership functions performed best, followed by trapezoid. Gaussian curve and generalized bell-shaped membership functions performed also well.

As an optimization method, the back-propagation method was used. Fig. 3 shows the generated ANFIS model structure. Its layered structure from left to right is the following:

 Layer1. Input neurons: for input neurons, three environmental components were used.

 Layer2. Input membership functions: three gaussian membership functions for each input neuron

 Layer3. Fuzzy rule left hand sides: each connected to 3 input membership functions.

 Layer4. Output membership functions (right hand sides): the right hand side rules are in one to one relation with the left hand side rules.

 Layer5. Aggregated output: each output membership function gets aggregated with the weight they carry.

 Layer6. Output (decision-making)

In order to avoid overtraining cross-validation technique has been used. Because the given set of membership functions were not a good choice for modeling the training data the minimum cross-validation error occurred within the first epoch in some cases. This also indicated that either more data needed to be selected for training, or it was necessary to modify the membership functions (both the number of membership functions and their types). For four gaussian input membership functions, 400 epochs, linear output membership functions, the Sum Squared Error between the actual and desired outputs was 0.315.
In Fig. 4 the thick line represents training and thin line represents cross-validation. It can be easily observed that both the training and the cross validation curves are still decreasing after 400 epochs, but the decrease rate is very low.

Once the ANFIS is trained it would be useful to extract a small number of rules, which can reliably predict the impact of environmental assessment based on fuzzy membership function values. Of course extracting rules cannot further improve performance, but will increase speed and efficiency for further training.

A very important thing is the indeterminate nature of human resources expert decisions. This is why a very high accuracy of classification cannot be expected. The same expert may easily make different decisions on the same data at different times. It is widely believed that different experts are also likely to make different decisions even under the same circumstances. Moreover environmental changes may have their own influence on decision making, so periodic training on as recent data as possible is required. Therefore, the reported values cannot give information about the quality of the decisions that the system makes, only about the performance of following the decisions launched by the surveyed expert. This problem is present in firm environmental organizations as well: they don’t have a given model or formula to effectively evaluate expert performance.

5. Conclusions

The paper points out that that human like-decisions can be achieved based on neuro-fuzzy inference system for environmental assessment issue. Through association rules a handful of fuzzy rules were extracted, which have nearly as good performance as the original set of rules trained by the ANFIS for decision making. Because of environmental constraints, periodic system training is necessary to keep pace with the environmental challenges.

Based on this approach the aim of the paper consists in developing a model for environmental assessment, so that both will be reduced to a minimum the risks from the improper performance of decision making.
The developed model, represent an attempt to provide an explicit and comprehensive description of the concept of environmental assessment via computing techniques in order to reduce adverse effects on environmental and implicit the population. Using linguistic variables and linguistic rules, the model gives quantitative measures of environmental assessment. Then, the problem of sustainable decision-making becomes one of specifying priorities among basic indicators and designing appropriate policies that will guarantee sustainable progress.

The model proposed provides new insights of environmental assessment, and it may serve as a practical tool for decision-making and policy design at the local or regional levels.

Further investigations regarding the system suppose incorporating more representative environmental parameters after discussions with specialists. Thus the system will be able to provide a more concrete analysis of a studied environmental system.

This system permits incorporation of all information which may be to hand, however ambiguous or subjective it may be, and cope with the lack of precision that is a concomitant of this sort of decision making process. Environment assessment for varying activities performed by organizations requires a coherent approach, which cannot be simplistic, to the information held.

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7. References


