ESTIMATING GREENHOUSE GAS EMISSIONS USING COMPUTATIONAL INTELLIGENCE

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Abstract: This work proposes a Neuro-Fuzzy Intelligent System – ANFIS (Adaptive Network based Fuzzy Inference System) for the annual forecast of greenhouse gases emissions (GHG) into the atmosphere. The purpose of this work is to apply a Neuro-Fuzzy System for annual GHG forecasting based on existing emissions data including the last 37 years in Brazil. Such emissions concern tCO_2 (tons of carbon dioxide) resulting from fossil fuels consumption for energetic purposes, as well as those related to changes in the use of land, obtained from deforestation indexes. Economical and population growth index have been considered too. The system modeling took into account the definition of the input parameters for the forecast of the GHG measured in terms of tons of CO_2. Three input variables have been used to estimate the total tCO_2 one year ahead emissions. The ANFIS Neuro-Fuzzy Intelligent System is a hybrid system that enables learning capability in a Fuzzy inference system to model non-linear and complex processes in a vague information environment. The results indicate the Neural-Fuzzy System produces consistent estimates validated by actual test data.

1 INTRODUCTION

Human activities have produced inadvertent effects on weather and climate. Adding gases such as carbon dioxide and methane into the atmosphere has increased the greenhouse effect and contributed to global warming by raising the mean temperature of the Earth by about 0.5°C since the beginning of the 20th century.

More recently, chlorofluorocarbons (CFCs), which are used as refrigerants and in aerosol propellants, have been released into the atmosphere, reducing the amount of ozone worldwide and causing a thinning of the ozone layer over Antarctica around October. The potential consequences of these changes are vast. Global warming may cause sea level to rise, and the incidence of skin cancer may increase as a result of the reduction of ozone. In an effort to prevent such consequences, production of CFCs has been curtailed and many measures have been suggested to control emission of greenhouse gases, including the development of more efficient engines and the use of alternative energy sources such as solar energy and wind energy. The purpose of this paper is to apply Neuro-Fuzzy Systems for annual greenhouse gases emissions (GHG) forecasting. GHG estimates in other contexts have been considered by researchers using statistical regression and modeling (Ghorbani et alli, 2008), (Searchinger and Heimlich, 2007). Time series applications using computational intelligence have also been considered by the authors (Biondi et. Alli, 2004). This paper is organized in four sections. The first section is the present introduction. The second section describes the used Neuro-Fuzzy Model. Section three shows results and discussions and the paper ends with section four depicting results and future work.

2 ANFIS STRUCTURE

The ANFIS (Adaptive Network Based Fuzzy Inference System) structure is a Fuzzy inference

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system (Jang et alli, 1997), (Rutkowski,2004) . The ANFI structure is depicted in Figure 1.

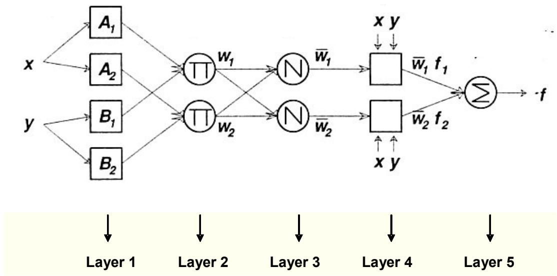

Figure 1: ANFI Structure.

The ANFI structure comprises five layers where layer one and four include adaptive nodes. The first layer nodes concern fuzzy sets related to the input variables whose outputs are membership functions. Layer two nodes are not adaptive and their task is to perform a normalization process which is part of a defuzzification procedure. Layer four leads to layer five that evaluates the system output including the final defuzzification in connection with layers 3 and 4. Details of the ANSI system can be found in (Jang et alli, 1997).

Learning procedures for the ANFI structure involve the parameters optimization of the adaptive nodes in layers one and four. The optimization procedure uses usually deepest descent gradient techniques (in connection with backpropagation techniques Jang et alli, 1997). Figure 2 depicts the ANFI structure used in this paper where the inputs are Var_1 : total emission at time t-1; Var_2 : GDP (Gross Domestic Product) at time t; Var_3 : Population at time t. The output is variable is the total emission at time t. For validation purposes, 20% of the available data was set apart for testing. In other words the system was trained with 80 % of the available data.

Figure 2: ANFI Structure Configuration.

Figure 3, 4 and 5 shows Population data, GDP data, and total emission data used in the ANSI prediction scheme. (Rodrigues, 2008).

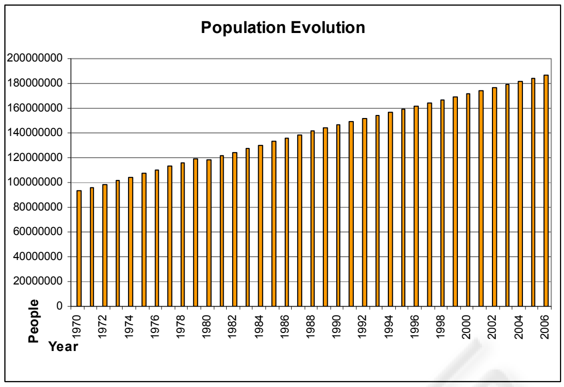

Figure 3: Population Evolution Data.

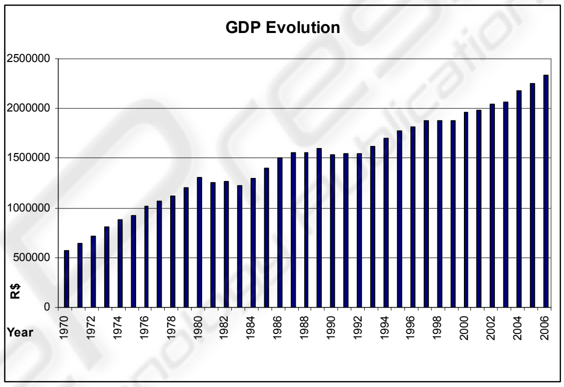

Figure 4: GDP Evolution Data.

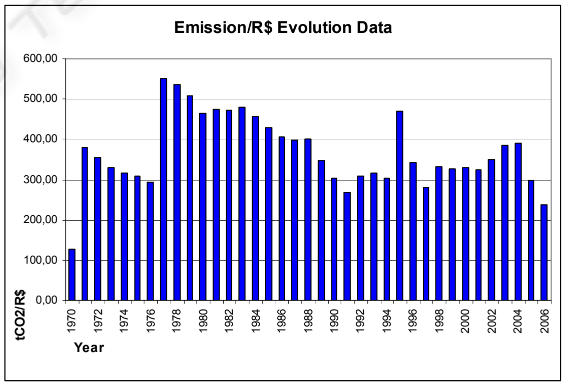

Figure 5: Emission/R$ Evolution Data.

3 RESULTS

Figure 6 shows the results comparing the trained data with ANFI estimated data.

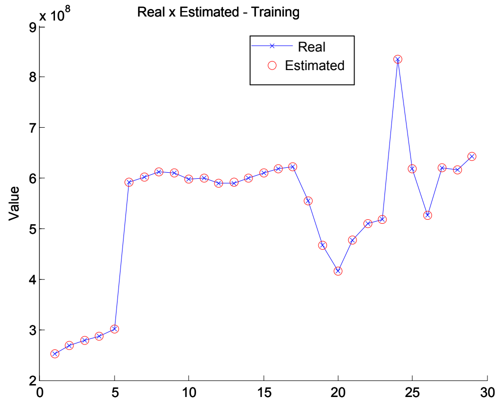

Figure 6: Trained x Estimated Data.

Figure 7 compares the ANFI estimates with the actual data for the validation set. Remember that the validation set is composed of data not used in the training of the ANSI structure. One can see an agreement concerning estimates and data.

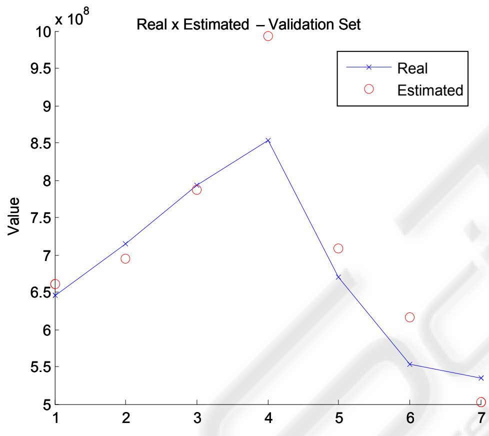

Figure 7: Validation Set x Estimated Data.

The average error for the validation set was about 7%. Figure 8 shows estimates comparison with data for all data i.e. training and validating set in order to give a better perspective of the whole estimation process.

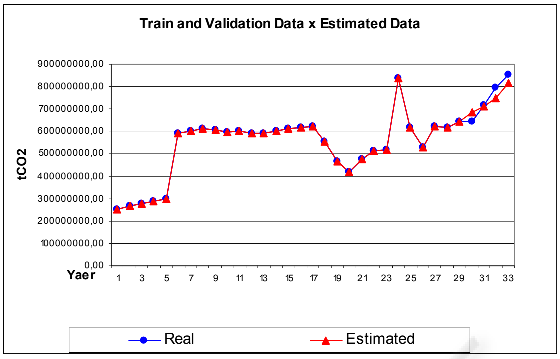

Figure 8: Trained and Validation Data x Estimated Data.

4 CONCLUSIONS

This paper applied a Neuro-Fuzzy approach for the estimation of greenhouse gas emissions. An ANFI structure was used whose inputs were GNP, Population and one step back emissions. Average errors were around 7 % for untrained data and the estimated emissions agreed with the used trained data. Future work concerns using data relating other type of emissions not considered in the present work.

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