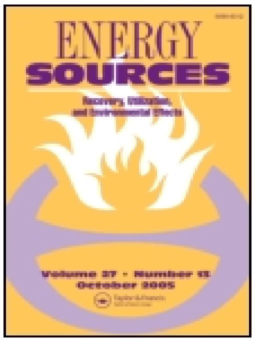

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Energy Sources, Part A: Recovery, Utilization, and Environmental Effects

ISSN: 1556-7036 (Print) 1556-7230 (Online) Journal homepage: http://www.tandfonline.com/loi/ueso20

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Energy Sources, Part A, 35:733–740, 2013

ISSN: 1556-7036 print/1556-7230 online
DOI: 10.1080/15567036.2010.514597

Forecasting of Greenhouse Gas Emissions in Serbia Using Artificial Neural Networks

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Serbia is attempting to synchronize its development with the basic assumptions of sustainable development and, consequently, data about environmental impact are necessary. The main goal of this study was to investigate and evaluate the possibility of using the artificial neural network technique for predicting the environmental indicators of sustainable development, in order to overcome the problem of incomplete data and to simulate various development scenarios and their environmental impact. Based on the results obtained, it may be concluded that an artificial neural network can be applied to model the greenhouse gas emissions as one of the environmental parameters of sustainable development.

Keywords: energy consumption, neural network, pressure indicators, Serbia, sustainable development

INTRODUCTION

Sustainable development has been defined as using resources in such a way that current needs are met, while the ability of future generations to meet their own needs is not compromised (World Commission on Environment and Development, 1987). Nearly all governments have committed themselves to sustainable development by integrating economic welfare, environmental quality, and social coherence (Böhringer and Jochem, 2007). The Republic of Serbia adopted its National Sustainable Development Strategy in 2008 (The Government of the Republic of Serbia, 2008).

Actual environmental impacts and other classes of environmental indicators represent an important dimension of sustainability; hence, specific environmental indicators have been developed for the needs of relevant interest groups. Sustainable development requires the development of models, which provide a quality response to the socio-economic needs and interests of the people, while at the same time eliminating or significantly reducing threats or damage to the environment and natural resources.

In this article, a neural network architecture is proposed to model, simulate, and predict greenhouse gas emissions (GHG) in European countries and the Republic of Serbia. By using country performance indicators as an input, the developed model can be used to simulate various

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development scenarios and the impact of various proactive measures, in order to support national-level decision-making on sustainable development.

METHOD

Serbia is located in the central part of the Balkan Peninsula, on the most important route linking Europe and Asia, occupying an area of 88,361 km^2. Its climate is temperate continental, with a gradual transition between the four seasons of the year.

Due to a relatively low degree of industrial activities in the last decade, Serbia is not considered as a significant emitter of carbon dioxide (The Government of the Republic of Serbia, 2008). In Serbia, this gas is primarily generated by fossil fuel combustion in power plants and central heating systems, in transport, and, to a lesser extent, partly by households with individual heating. Since there is no national inventory of greenhouse gases, the aim of this study was to develop a model for estimating the GHG emissions in Serbia using artificial neural networks (ANNs).

The process of ANN development followed a well known, standard methodology (Wasserman, 1993), which had already shown good results in modeling environmental-related problems (Boznar and Mlakar, 1998; Pocajt, 1999).

Once GHG emissions had been established as an output variable for the model, the input variables had to be selected. Since it had been previously shown for Turkey that models based on economic indicators give satisfactory accuracy (Say and Yücel, 2006; Sözen et al., 2009), the gross domestic product (GDP) was an apparent first choice for an input parameter. However, the problem is far too complex to be simulated with only one input parameter, as shown in recent research (Jobert et al., 2010). Thus, more parameters, from the industrial profile of the country and the energy intensity of production to the habits of citizens, have to be taken into account. Moreover, in defining the inputs, the availability of input and output datasets is a must that needs to be considered.

Consequently, the share of renewable sources of energy, the gross domestic product, the gross energy consumption, and energy intensity were selected as the input parameters. Keeping in mind that neural networks generally achieve better performances with normalized values, the parameters were normalized in the following way: (1) the GDP was first normalized *per capita* and then to the EU 27 average; (2) the gross energy consumption was normalized *per capita*; and (3) the GHG emissions were normalized *per capita*.

To create training and test sets for the ANN model, the information published by Eurostat (2010) was used for selected European countries and information from the International Energy Agency (2009) and the Statistical Office of the Republic of Serbia (2010) was used for Serbia. The information can be regarded as sufficiently reliable and precise.

The software tool NeuroShell 2 (1993) was used for neural network design and training. NeuroShell is a leading software environment for developing diversified neural network architectures. Moreover, it already has a record of successful applications in atmospheric pollution modeling (Pocajt and Cvijović, 1997; Pocajt, 1999; Boznar and Mlakar, 2001).

THE MODEL

Data for the selected European countries for the years 1999–2001 were used as the training set for the neural network and the data for the same countries for the years 2002–2007 were used as the test set. The training dataset for the year 1999 is presented in Table 1. Figure 1 shows the

TABLE 1
An Example of a Training Dataset (Year 1999)

	Inputs				*Output*
Region/Country	*ShareRen*[a]	*GDPpcN*[b]	*GrossCpc*[c]	*EnInt*[d]	*CO_2pc*[e]
EU (27 countries)	5.60	1.00	3.55	193.20	10.48
EU (15 countries)	5.70	1.21	4.75	172.43	13.38
Belgium	1.30	1.29	5.98	251.74	14.14
Bulgaria	3.50	0.09	2.21	1,398.66	8.45
Czech Republic	1.90	0.31	3.74	649.37	13.67
Denmark	9.70	1.70	3.78	119.77	13.66
Germany	2.50	1.31	4.15	170.55	12.31
Estonia	10.40	0.24	3.62	895.11	13.27
Ireland	1.60	1.45	3.68	143.20	18.02
Greece	5.30	0.66	2.47	203.51	11.33
Spain	5.20	0.82	2.97	197.35	9.34
France	7.20	1.24	4.25	184.52	9.33
Italy	5.80	1.09	3.02	149.52	9.59
Cyprus	1.90	0.76	3.33	236.88	13.08
Latvia	31.80	0.19	1.65	498.06	4.48
Lithuania	7.90	0.18	2.23	664.78	5.88
Luxembourg	1.30	2.63	8.07	169.99	22.04
Hungary	1.90	0.26	2.49	515.48	7.80
Netherlands	2.30	1.38	4.81	188.35	13.65
Austria	22.90	1.36	3.67	146.26	10.14
Poland	4.00	0.26	2.43	526.46	10.36
Portugal	13.50	0.63	2.45	211.53	8.25
Romania	11.90	0.09	1.64	934.56	5.85
Slovenia	8.60	0.57	3.25	313.47	9.44
Slovakia	2.70	0.21	3.22	800.02	9.17
Finland	22.10	1.34	6.37	261.09	13.86
Sweden	27.00	1.57	5.70	197.64	7.87
United Kingdom	1.10	1.42	3.91	148.62	11.46
Croatia	11.30	0.27	1.76	410.82	5.76
Turkey	15.00	0.24	1.08	262.31	3.90
Iceland	71.20	1.75	11.17	341.00	13.64
Norway	44.70	2.13	6.02	151.29	12.10
Switzerland	16.90	1.97	3.66	99.77	7.36

[a] Share of renewable energy (%).
[b] Gross Domestic Product per capita normalized to the EU 27 average.
[c] Gross Energy Consumption in tonnes of oil equivalent per capita.
[d] Energy intensity in kilograms of oil equivalent per 1,000 € of value produced.
[e] GHG emissions/capita (CO_2pc) in tonnes of CO_2 equivalent.

performance of the ANN on the training dataset by comparing the results given by the model and the actual emissions of GHGs. The results given by the model and the correlation factor may be regarded as good.

The input parameters, actual GHG emissions, the neural network predictions, and the relative errors for 2002 are presented in Table 2. It should be emphasized that the input data belong to the test set, i.e., that the dataset introduced was completely new for the ANN and is, consequently, an unbiased test of the capabilities of the model to make predictions.

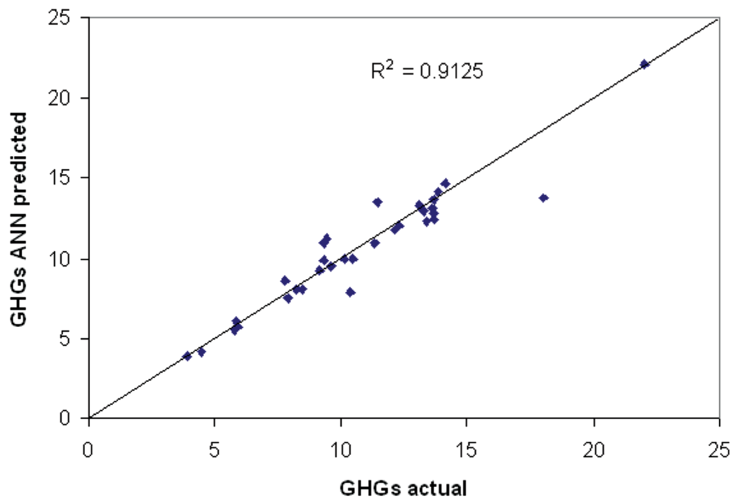

FIGURE 1 Comparison of the actual (measured) data and the ANN results for the GHG emissions of European countries in 1999. (color figure available online)

The comparison of the actual data and the ANN results for GHG emissions for the same year is given in Figure 2. It may be concluded that the correspondence between the values predicted by the model and the actual measured ones was satisfactory, having a relative error below 10% in most cases. Some notable exceptions include overestimations by the model for Hungary, for which the reported level of GHG emissions is consistently far lower than in similar countries; Croatia, which seems to have a peculiar, service-oriented structure of industry and consumption; and Switzerland, probably as a result of the smallest energy intensity in Europe.

The same comparison for Bulgaria is given in Figure 3. Bulgaria was selected as a country of special interest because its level of economic development, industry structure, climate, and energy intensity and consequently the input data are very similar to those of Serbia (Table 3). It may be noted that the ANN showed good results for Bulgaria. Even in predicting GHG emissions 5 years and more in the future, the relative error was less than 10%. Therefore, good results for Serbia might be expected.

Finally, the available input data for Serbia for the period 2005–2007 was provided to the ANN and compared with actual GHG emissions. As opposed to other European countries, there were no measured/reported actual data for GHG emissions for Serbia, so they were calculated from the CO_2 emissions. Although carbon dioxide is by far the most important greenhouse gas, accounting for about 82.5% of the global warming potential (Eurostat, 2007), this means that actual GHG emissions for Serbia are an estimate as well.

As shown in Table 3, the predictions obtained are in good correspondence with the actual (calculated) values, with an exception for 2007, where the ANN predicted lower emissions, probably because of the reported decrease of energy consumption, while the emission level actually increased. However, the reported decrease of energy consumption in 2007 is itself dubious, since it is opposite to the long-term trend of increase in energy consumption per capita in Serbia.

Based on the results obtained, it may be concluded that ANNs can be applied for modeling GHG emissions as one of the environmental parameters of sustainable development. The fact that the problem is complex, most probably highly non-linear, and without explicit mathematical functions that define the relationships among the variables, combined with the good availability

TABLE 2
An Example of a Test Dataset (Year 2002)

					CO_2pc		
Region/Country	*ShareRen,* %	*GDPpcN,* € *per Capita*	*GrossCpc, 1,000 t Oil eq*	*EnInt, kg oe per 1,000* €	*Actual*[a]	*ANN*	*RelErr,* %
EU (27 countries)	5.7	1.00	3.63	185.00	10.45	10.12	3.19
EU (15 countries)	5.8	1.20	4.82	165.52	13.30	12.59	5.38
Belgium	1.5	1.27	5.67	226.90	13.86	14.06	1.41
Bulgaria	4.4	0.10	2.41	1,274.82	8.43	8.74	3.68
Czech Republic	2	0.38	4.12	654.50	14.21	14.97	5.35
Denmark	12.4	1.68	3.69	112.65	12.79	12.02	5.97
Germany	3.4	1.27	4.19	165.51	12.21	11.75	3.74
Estonia	11	0.28	3.65	701.48	13.27	10.90	17.92
Ireland	1.7	1.62	3.92	129.63	17.63	16.23	7.93
Greece	4.7	0.70	2.72	200.83	11.65	11.06	5.10
Spain	5.4	0.86	3.19	194.97	9.84	9.97	1.34
France	6.3	1.22	4.35	180.25	8.94	11.24	25.73
Italy	5.3	1.11	3.06	143.02	9.75	9.78	0.25
Cyprus	1.8	0.77	3.45	227.75	13.22	13.33	0.83
Latvia	31.3	0.20	1.71	411.46	4.58	5.05	10.21
Lithuania	8.1	0.21	2.49	611.91	5.93	6.49	9.48
Luxembourg	1.4	2.62	8.99	169.94	25.54	22.53	11.78
Hungary	3.4	0.34	2.55	459.74	7.67	15.09	96.87
Netherlands	2.6	1.40	4.95	186.99	13.38	13.10	2.07
Austria	22.1	1.32	3.90	148.38	10.79	8.12	24.77
Poland	4.6	0.27	2.34	468.98	9.71	9.94	2.31
Portugal	13.9	0.64	2.54	208.97	8.59	8.10	5.73
Romania	9.7	0.11	1.76	858.30	6.72	5.79	13.84
Slovenia	10.5	0.60	3.43	298.51	10.06	10.88	8.16
Slovakia	3.7	0.23	3.59	809.63	9.11	11.71	28.61
Finland	21.8	1.35	6.78	255.13	14.79	17.30	16.95
Sweden	26.3	1.44	5.73	185.16	7.81	8.39	7.49
United Kingdom	1.2	1.40	3.83	135.33	11.07	13.54	22.25
Croatia	9.2	0.31	1.86	375.39	6.33	9.37	48.03
Turkey	13.4	0.18	1.10	259.99	3.93	3.86	1.80
Iceland	72.7	1.60	11.82	345.53	13.02	13.03	0.15
Norway	51.7	2.20	5.37	128.57	11.78	10.19	13.47
Switzerland	17.2	1.98	3.65	96.22	7.10	10.45	47.25

[a]Actual denotes the measured GHG emissions and ANN the predictions made by the model.

of reliable data to create training sets and test sets, favors further research in this direction. Also, ANN models can be a useful tool to simulate various development scenarios, the impact of measures implemented by the government and industry and, hence, to support national- and international-level decision-making on sustainable development. This is especially important for countries such as Serbia, which need to foster dynamic development, but also lack many of the data for the environmental parameters of sustainable development. The capability of ANNs to provide satisfactory results, even when working with relatively scarce and missing data, can prove to be of high practical importance.

Further research is planned to include the modeling of other sustainable development parameters, such as particulate matter, ozone and acid oxide emissions, and municipal waste generation.

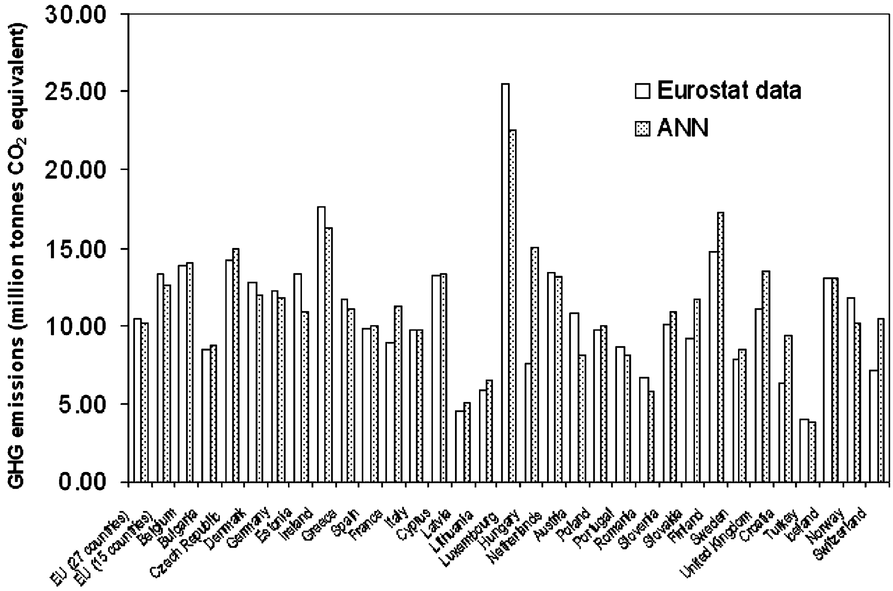

FIGURE 2 Comparison of the actual data and the ANN results of GHG emissions for EU regions/countries for 2002.

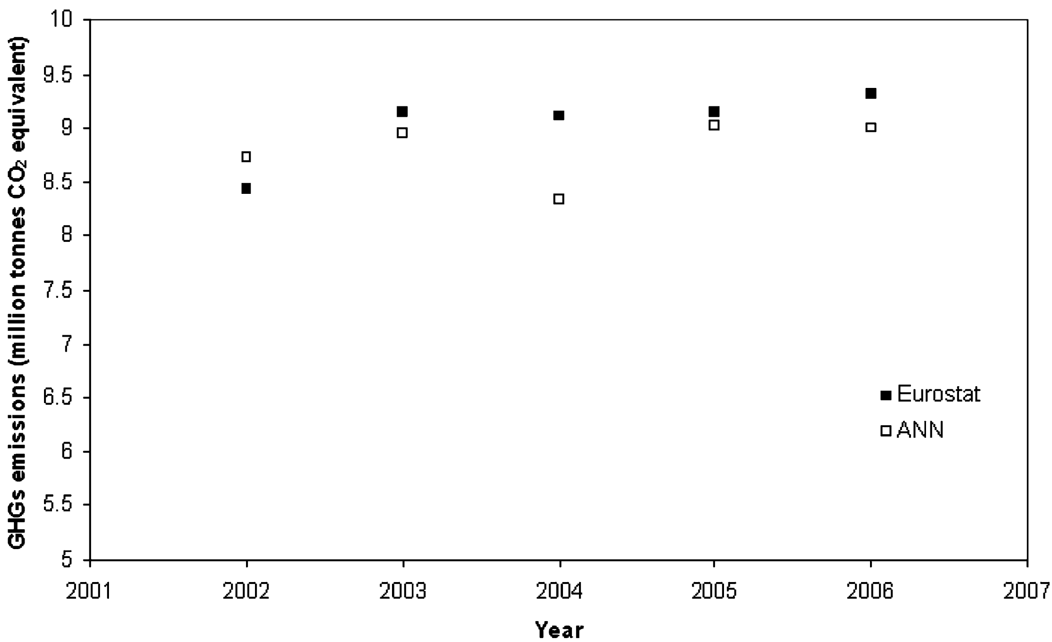

FIGURE 3 Comparison of the actual data and the ANN results for the tested years for Bulgaria.

TABLE 3
Comparison of the Input Data and GHG Emissions for Bulgaria and Serbia

Country	*ShareRen, %*	*GDPpcN, € per Capita*	*GrossCpc, 1,000 t Oil eq*	*EnInt, kg oe per 1,000 €*	*CO_2pc* Actual, Calculated	*CO_2pc* ANN, Predicted
	2005	*2005*	*2005*	*2005*	*2005*	*2005*
Bulgaria	5.6	0.12	2.58	1,127	9.15*	9.02
Serbia	7.0	0.12	2.07	1,530	7.14**	6.90
	2006	*2006*	*2006*	*2006*	*2006*	*2006*
Bulgaria	5.5	0.14	2.66	1,090	9.11*	9.00
Serbia	6.6	0.13	2.29	1,200	7.61**	7.41
	2007	*2007*	*2007*	*2007*	*2007*	*2007*
Serbia	5.7	0.16	2.14	1,200	7.91**	6.61

*Eurostat data.
**Predicted on the basis of CO_2 emission.

Also, in order to increase the quality of the model itself, other ANN architectures will be tested, such as recurrent neural networks, which tend to exhibit better results with time series.

ACKNOWLEDGMENTS

The authors acknowledge funding from the Ministry of Education, Science and Technological Development of the Republic of Serbia, Fundamental Science Project No. 172007.

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