

The forecasting of municipal waste generation using artificial neural networks and sustainability indicators

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Abstract The feasibility of modeling municipal waste generation (MWG) for countries at different levels of development using artificial neural networks (ANN) and selected generic indicators of sustainability was investigated. The main goals of this research were to develop ANN-based models for predicting MWG, to overcome the problem of incomplete MWG data, which is notable in developing countries, and to provide a new method for the planning of municipal solid waste management systems as well as for the simulation of various other scenarios. Data from 26 European countries was used in this study as training, test and validation datasets for the developing of ANN models. Since this kind of modeling is particularly important for developing countries where MWG data is missing or incomplete, emphasis was placed on modeling of MWG for Bulgaria and Serbia. Based on a comparison of actual MWG data with predictions given by the model, we show that ANNs can be applied successfully to modeling and forecasting MWG on a national scale. Moreover, the scope for possible application of the model is broad, since it uses generic indicators of sustainability such as gross domestic product, domestic material consumption and resource productivity, and performs well for countries

with highly diversified levels of economic development, industrial structure, productivity and output.

Keywords Waste generation · Modeling · Neural networks · European Union · Bulgaria · Serbia

Introduction

Urban waste management became recognized as a problem in the developing world during the 1990s, due to the negative impact of degrading wastes and associated vermin on the quality of life, and productivity, in densely populated centers (Schubeler 1996). The amount and composition of waste generated comprise the basic information needed for the planning, operation and optimization of waste management systems (Beigl et al. 2008). Poor management of solid waste may result in serious urban, sanitary and environmental problems such as unpleasant odors and risk of explosion in landfill areas, as well as groundwater contamination because of leachate percolation (Mor et al. 2006).

Solid waste management in developing countries around the world has been reported on by several researchers (Berkun et al. 2005; Henry et al. 2006; Chung and Lo 2008; Gamze Turan et al. 2009; Ngoc and Schnitzer 2009; Shekdar 2009). A number of studies highlight a lack of the data that are necessary for good organization of waste management systems in some developing European countries (Hristovski et al. 2007; Vego et al. 2008).

In Serbia, in most cases, the unofficial landfills found in rural environments are mostly the outcome of the meager funds allocated to improving the quality of the waste collecting system, as well as the poor organization of waste management at a local level (Dedijer et al. 2007). The

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consequences of poor organization of waste management in Serbia are the 164 official landfills and an extremely large number ($\sim 4,400$) of unofficial landfills [Serbian Environmental Protection Agency (SEPA) 2010].

Mathematical models of sustainable development (Phillips 2010) and environment-related problems (e.g., land-use changes) (Yin and Xiang 2010) are very important. Prediction of the quantity of municipal solid waste (MSW) is crucial for the planning of municipal solid waste management systems (MSWMS), and the development of reliable models, such as data-driven models, for this purpose would be a useful advancement in the practice of MSWMS (Noori et al. 2009).

The concept of artificial neural networks (ANN) was discovered nearly 50 years ago, but it is only in the last 20 years that application software has been developed to handle practical problems (Kalogirou 2003). An ANN can be visualized as a black-box, non-linear approach, where a collection of inputs are presented to the network and one or more results (outputs) are produced.

In recent years, ANNs have become a popular and useful tool for modeling environmental systems. ANN modeling is an effective way to attain the environmental parameters for a chosen area, based on economic, industrial, and demographic parameters that are monitored continuously throughout the world. For example, ANNs have already been used successfully for modeling solid waste related problems: for example, weekly solid waste prediction (Noori et al. 2009), predicting the rate of medical waste generation (Jahandideh et al. 2009), and modeling the leaching behavior of solidified wastes (Bayar et al. 2009).

This paper presents the development and evaluation of an ANN-based model for municipal waste generated (MWG) at a national level, for countries at different levels of economic development and industrial structure. Two different ANN architectures, back-propagation (BP) and general regression neural network (GRNN), were proposed for this model and the results are compared and analyzed. To cover a broad scope of levels of economic development and diversified industry structures, data from 26 European countries were used in this study as training, test and validation datasets in developing the ANN models. In general, the 15 countries of the “old” European Union, Switzerland and Norway represent more developed economies, whilst most of the newer members and accessing countries correspond to new and developing economies.

Since this kind of modeling is particularly important for developing countries where MWG data is missing or incomplete, emphasis is placed on modeling of MWG for Bulgaria and Serbia, where there is no measured data for MWG but there are estimations made by SEPA. Thus, the developed models were finally applied to MWG

forecasting for Bulgaria and Serbia for the years 2006–2009, and the results compared with actual values.

Materials and methods

Artificial neural network models

ANNs are information-processing algorithms inspired by the way biological nervous systems make generalizations from similar situations, such as learning from past experience, and produce decisions out of incomplete knowledge of states with large inherent complexities and nonlinearities (Bayar et al. 2009). Neurons usually operate in parallel and are configured in regular architectures. They are often organized in layers, and feedback connections both within the layer and toward adjacent layers are allowed. The strength of each connection is expressed by a numerical value called a weight, which can be updated (Jahandideh et al. 2009). The ANN architecture most commonly used is composed of three layers. Many theoretical and experimental studies have shown that a single hidden layer is sufficient for ANN to approximate any complex nonlinear function (Noori et al. 2010). A general ANN structure and elements of the artificial neuron are shown in Fig. 1.

A learning algorithm is defined as a procedure that consists of adjusting the weights and biases of a network to minimize an error function between network outputs, for a given set of inputs, and the correct outputs. There are different learning algorithms, one of the most popular being the BP algorithm, which has different variations (Sözen et al. 2009).

The process of ANN development shown in Fig. 2 follows the methodology that has already shown good results

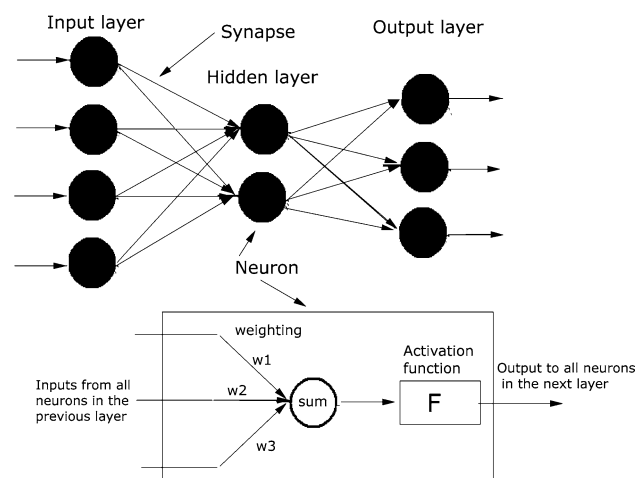


Fig. 1 Elements of an artificial neural network (ANN) architecture and artificial neuron

in modeling of greenhouse gas emissions (Radojević et al. 2010).

Defining input and output parameters

Since it has been shown previously that environmental ANN models based on economic and sustainability indicators can achieve good accuracy (Sözen and Arcaclioglu 2007; Sözen et al. 2009; Radojević et al. 2010), gross domestic product (GDP) was chosen as the basic input parameter. Domestic material consumption and resource productivity were also selected as input parameters (Table 1), as representative indicators of material use that is connected directly with waste generation.

The parameter domestic material consumption (DMC) is defined as the total amount of material used directly in an economy. DMC equals direct material input (DMI) minus exports. DMI measures the direct input of materials for use in the economy. DMI equals domestic extraction (DE) plus imports. Resource productivity (RP) is GDP divided by DMC (Eurostat 2010a).

Since ANN models generally achieve substantially better performance with normalized values, GDP was first

normalized per capita and then with the EU 27 average; DMC was normalized per capita. The output parameter was MWG in kilograms per capita.

Datasets

To create training- and test-sets for the ANN model, consisting of 26 European countries plus the EU (27 countries, EU27) and the “old” EU (15 countries, EU15) as groups, a recent report published by Eurostat (Eurostat 2010a, b, c, d) was used for the selected European countries. Data from the years 2000 to 2002 was used as the training and test datasets. Data from 2003 to 2005 was used as the validation dataset. An example of the training dataset for the year 2000 is presented in Table 2.

For Serbia, information from SEPA (2010) and the Statistical Office of the Republic of Serbia (2008, 2009, 2010) was used.

Although the Serbian Statistical Bureau does not report DMC as statistical data, it has been published by Eurostat; therefore the DMC for Serbia was calculated using the formula given by Weisz et al. (2006), i.e., $DMC = \text{domestic extraction} + \text{imports} - \text{exports}$. The categories of material flows needed to calculate the domestic extraction are given in Table 3 (Weisz et al. 2006). To avoid the influence of currency fluctuations to the Euro, the GDPpc values for Serbia were calculated using 2006 prices. The datasets for Serbia for the years 2006–2009 are presented in Table 4.

ANN architecture

For neural network design and training, the software tool NeuroShell (Ward Systems Group Inc. 2010) was used. NeuroShell is a leading software environment for developing diversified neural network architectures, with high flexibility, well-proven training algorithms and optimization utilities, which has numerous advantages over building neural network from scratch. It already has a history of successful applications in modeling leaching behavior of solidified waste (Bayar et al. 2009).

The most frequently used ANN architecture is the BP network. BP networks are a supervised type of network, trained with both inputs and outputs. A BP network learns by example, i.e., a repeated processing training file containing a series of input vectors and the target output vector for each case should be provided. During each run of the training file, the network compares the target result with the actual result and calculates the error (Bayar et al. 2009). Architectures of BP networks include feedforward (standard), recurrent, feedforward with multiple hidden slabs and jump connection networks. The first type of BP architectures, in which each layer is connected to the immediately previous layer (feed-forward), was used in

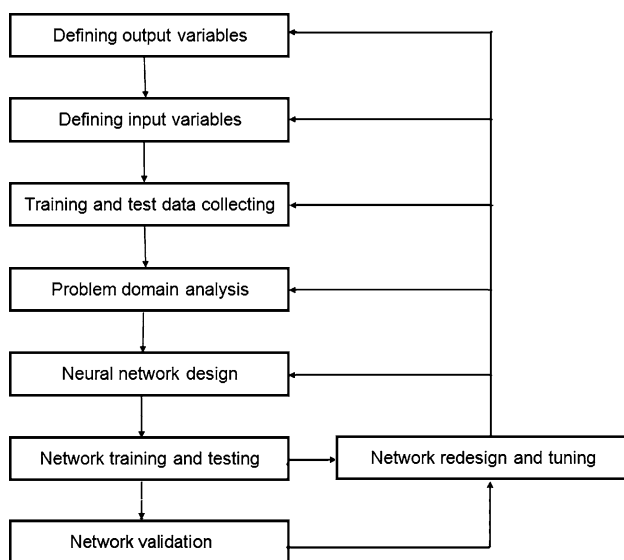


Fig. 2 The process of ANN development

Table 1 Input and output parameters of municipal waste generation (MWG) artificial neural network (ANN) model

Input parameter		Output parameter	
Gross domestic product per capita (GDPpc)	Compared to GDPpc (EU27)	MWG	kg per capita
Domestic material consumption (DMC)	kg per capita		
Resource productivity (RP)	€ per kg		

Table 2 Training dataset for the year 2000

Region/country	GDPpc compared to GDPpc (EU27)	DMC (kg per capita)	RP (€ per kg)	MWG (kg per capita)
EU (27 countries)	1.00	15,480 ^a	1.23 ^b	524
EU (15 countries)	1.21	20,210 ^a	1.41 ^b	569
Belgium	1.29 ^c	18,856 ^a	1.30 ^b	474
Bulgaria	0.09	12,282	0.14	516
Czech Republic	0.31	18,039	0.33	334
Denmark	1.70	25,282	1.29	665
Germany	1.31	17,728	1.42	643 ^d
Estonia	0.24	21,753	0.20	440 ^d
Ireland	1.45	31,368	0.88	603
Greece	0.66	16,080	0.79	408
Spain	0.82	17,244	0.91	662
France	1.24	14,488	1.64	516
Italy	1.09	16,943	1.23	509
Cyprus	0.76	26,333 ^a	0.55 ^b	680
Latvia	0.19	8,075	0.44	270 ^d
Lithuania	0.18	8,223	0.43	363
Hungary	0.26	10,927	0.47	445
Austria	1.36	19,006	1.36	581
Poland	0.26	13,190	0.36	316
Portugal	0.63	18,475	0.65	472
Romania	0.09	7,658	0.23	363
Slovenia	0.57	17,024	0.63	513 ^d
Slovakia	0.21	9,635	0.42	254 ^e
Finland	1.34	34,471	0.74	503
Sweden	1.57	13,444	2.24	428
United Kingdom	1.42	11,906	2.29	578
Norway	2.13	20,739	1.97	615 ^e
Switzerland	1.97	12,441	3.04	657

^a Estimated data (Eurostat 2010a)

^b Estimated data (Eurostat 2010c)

^c Estimated data (Eurostat 2010b)

^d Estimated data (Eurostat 2010d)

^e Methodology different from standard EU methodology (Eurostat 2010d)

this study because a three-layer BP network with standard connections is considered suitable for almost all problems (Kalogirou 2003).

In addition to BP architecture, GRNN architecture was used to create the municipal waste generation ANN model, because GRNNs can respond much better than BP neural networks to some types of problems (Pocajt 1999; Kalogirou 2003). A GRNN is a feedforward neural network based on non-linear regression theory, consisting of an input layer, hidden layer and output layer—the hidden layer consisting of the pattern layer and the summation layer. GRNNs work by measuring how far a given sample pattern is from the patterns in the training set in N dimensional space, where N is the number of inputs in the problem. The training of the GRNN is quite different from the training used in other neural networks, being completed after presentation of each input–output vector pair from the training data set to the GRNN input layer only once (Kalogirou 2003).

The BP and GRNN architectures used for MWG models are presented in Fig. 3a, b.

For both architectures, the number of neurons in the input and output layer is equal to the number of input and output parameters that have been used in the ANN model. In this case there are three neurons in the input and one neuron in the output layer. A rule that applies to the hidden layer in the GRNN model is that the number of neurons must be equal to the number of data series in the training sets that will be used for model training. Therefore, the number of neurons in the hidden layer was 84. The number of neurons in the hidden layer in the BP model was 10, which is the default number of hidden neurons when a model has three inputs and one output parameter.

Results and discussion

In the implementation phase, the GRNN network had very short training periods, less than a second, unlike the BP ANN, for which the learning time ranged from one to several hours. Figure 4 shows the performance of the BP

Table 3 Classification of material flows (Weisz et al. 2006)

Main material categories	Subcategories	Aggregated items
Biomass	Food	All potentially edible biomass from cropland plus traded food products
	Feed	All biomass from grassland, by-products and crops exclusively used for feeding livestock plus traded fodder
	Animals	All caught wild animals (in particular fish catch) and all traded livestock and animal products, including fish
	Wood	Harvested wood and traded wood-based products including paper, furniture, etc
	Other biomass	Fibres and highly manufactured traded products predominantly from biomass
Fossil fuels	Coal	All types of coal
	Oil	All types of oil
	Natural gas	All types of natural gas
	Other fossils	Peat and highly manufactured traded products predominantly from fossil fuels
	Industrial minerals	Industrial minerals
	Ores	All non-metallic minerals used predominantly for industrial processes (excluding fossil fuels)
Construction minerals	Construction minerals	All minerals used primarily in construction

Table 4 Datasets for Serbia

Year	Input parameters			Actual output
	GDPpc ^a compared to GDPpc (EU27)	DMC (kg per capita)	RP (€ per kg)	MWG (kg per capita)
2006	0.13	12,216	0.26	233
2007	0.13	12,321	0.27	280
2008	0.14	13,397	0.26	350
2009	0.15	12,624	0.27	360

^a Calculated using 2006 prices

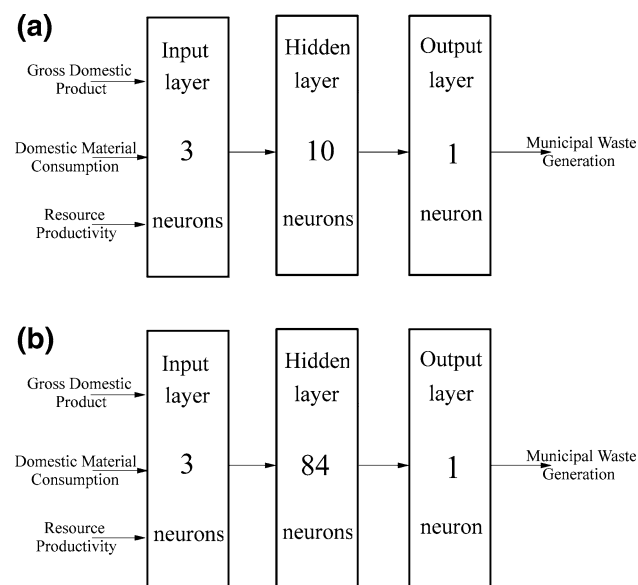


Fig. 3 **a** Back-projection (BP) ANN architecture for municipal waste generation ANN model. **b** General regression neural network (GRNN) architecture for municipal waste generation (MWG) ANN model

ANN and GRNN models on the training dataset (years 2000–2002), by comparing the results given by the model to the known actual MWG values.

The results given by the models and correlation factors can be regarded as very good. The GRNN model has an excellent value of R^2 (0.981)—indeed slightly better than the BP ANN (0.930). The BP ANN model made excellent predictions (relative error $\leq 1\%$) for Cyprus (for all 3 years), Estonia and Switzerland (for 2 years), Romania, Slovakia, Czech Republic, Ireland, Finland, Sweden, Norway and the European Union (for 1 year). The GRNN model made 74 % predictions with mean relative error $\leq 1\%$. For many countries, the GRNN model made predictions with no error: Denmark, Ireland and Norway (for all 3 years), Czech Republic, Finland, Sweden, Italy, Hungary, France, Switzerland and the European Union (for 2 years), United Kingdom, Cyprus, Germany and Austria (for 1 year).

The validation datasets presented completely new data to the ANNs models, and demonstrate the realistic capability of the model to make predictions successfully. The results of the validation datasets (years 2003–2004) are

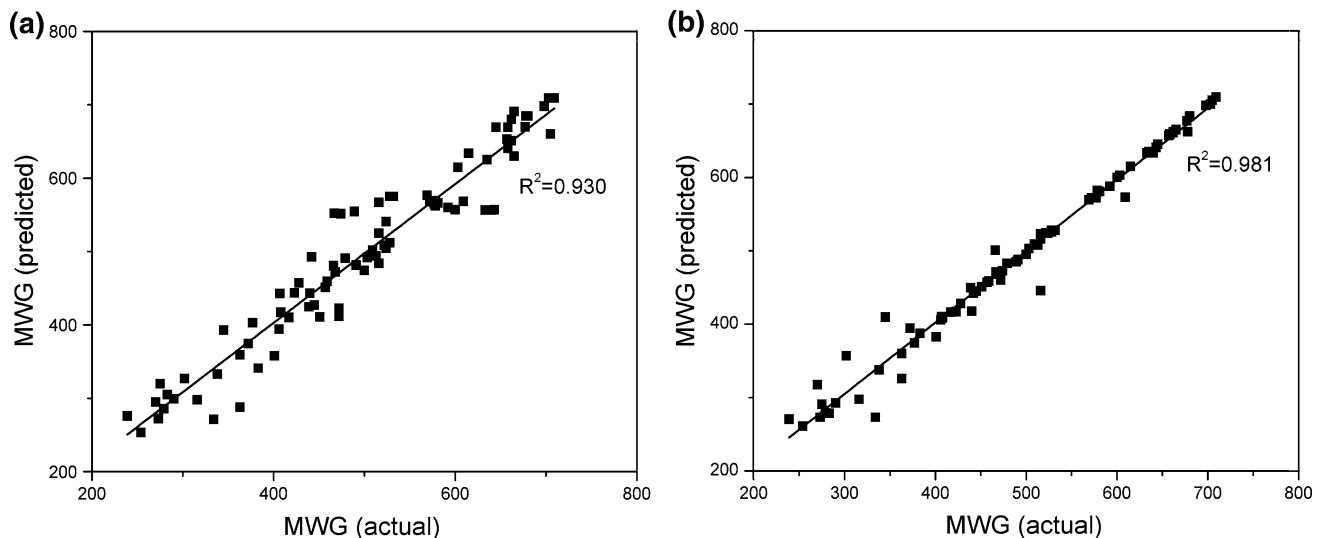


Fig. 4 Comparison of actual (measured) data and modeled results for the MWG of European countries for 2000–2002 (training dataset). **a** BP ANN, **b** GRNN

presented in Figs. 5 and 6. An example of the validation dataset for the year 2005 including the input parameters, actual MWG, neural network predictions and relative errors is presented in Table 5.

The GRNN model made much better predictions, with the R^2 value varying from 0.798 to 0.843, compared to the BP ANN with an R^2 value in the range of 0.613–0.647 (Figs. 5, 6). The BP ANN model made 44 % of its predictions satisfactorily with a relative error of less than 10 %. In the case of Cyprus, Austria, Denmark, Slovakia, Norway and the European Union (15 countries), the predictions of the BP ANN model had a relative error of less than 10 % for all 3 years. For the same validation dataset, the GRNN model made 69 % of its predictions satisfactorily (relative error ≤ 10 %). The quality of the GRNN predictions was stable for all three validation years, unlike the BP ANN predictions (Table 6).

Based on the results obtained by training and validation of the ANN models, it can be concluded that the tested GRNN network provides considerably better predictions of MWG than the tested configuration of the BP network. Since varying BP architecture and parameters is beyond the scope of this research, further analysis in this study will relate to the GRNN model only.

The deviation between the actual data and predicted values given by the GRNN model for some countries (Table 5) is a consequence of the quality of the data used for training and comparison rather than an inaccuracy of the model. In the case of Belgium, the data used for input parameters, except GDP, and MWG for training years was estimated (Table 2), which resulted in a deviation between the actual and predicted values for all three validation years (Fig. 5b, 6b), e.g., the relative error in year 2005 was

26.5 % (Table 5). The MWG data for Latvia and Slovenia used for model training was also estimated (Table 2), again resulting in large relative errors for all three validation years for Latvia (Fig. 5b, 6b; Table 5) and a large relative error for 2003 for Slovenia (Fig. 5b).

In the case of Slovakia, the data for MWG until 2001 was collected from the National Waste Catalogue and from 2002 onwards from The European List of Waste (Eurostat 2010d). Consequently, the training data for Slovakia for the years 2000 and 2001 was not standard, resulting in the relative error in the year 2003 (Fig. 5b) and in the year 2005 of 48.8 % (Table 5). Similarly, in Norway prior to 2001 the figures for MWG included all waste collected and handled by municipalities and were not limited to household waste, but included production waste as well (Eurostat 2010d). The non-standard methodology in the case of Norway resulted in a relative error of 16.4 % for 2005 (Table 5).

For Poland and Romania, the data in the validation datasets used for comparison with ANN models were estimated, not measured (Eurostat 2010d). This could well explain the large relative errors of the predicted values and officially estimated data for those two countries (Figs. 5b, 6b), e.g., in the case of Romania the relative error was 32.6 % for 2005 (Table 5).

In the case of Greece, data for GDPpc on Eurostat for years 2004 and 2005 are marked as “Provisional values”, because of the inaccurate reporting on the economic situation in Greece by the government. For those years the GRNN model made predictions with relative errors larger than 50 % (Fig. 6b; Table 5), while for 2003, for which the GDP value for Greece is considered reliable, the GRNN model made a good prediction with the relative error being just 2.9 %.

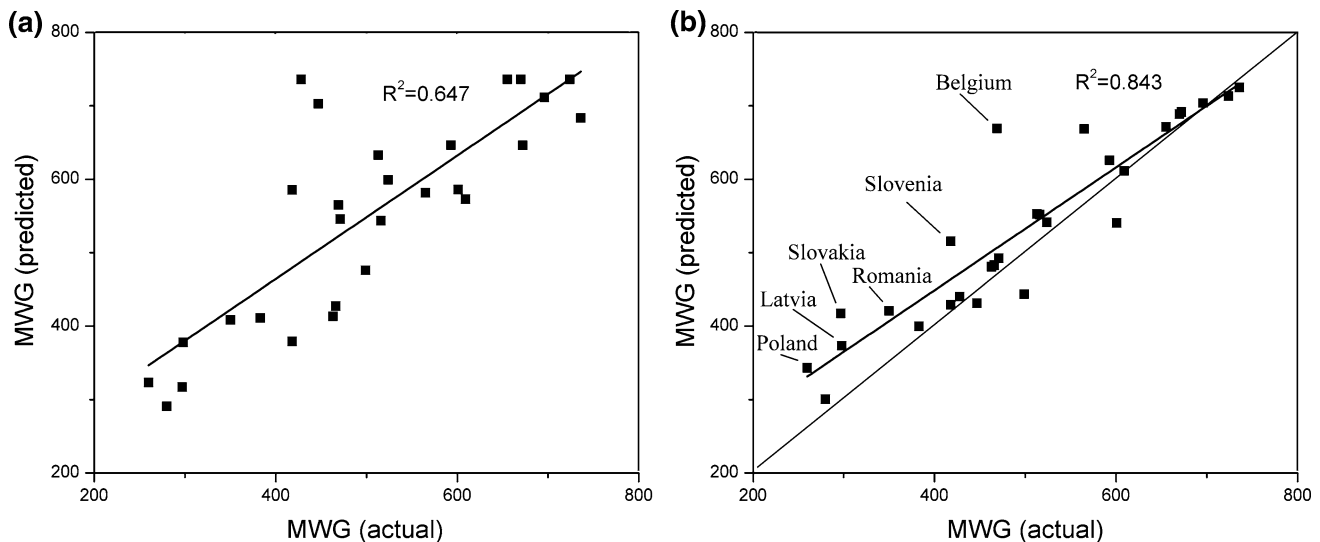


Fig. 5 Comparison of actual (measured) data and ANN results for MWG of European countries for year 2003 (validation dataset). **a** BP ANN, **b** GRNN

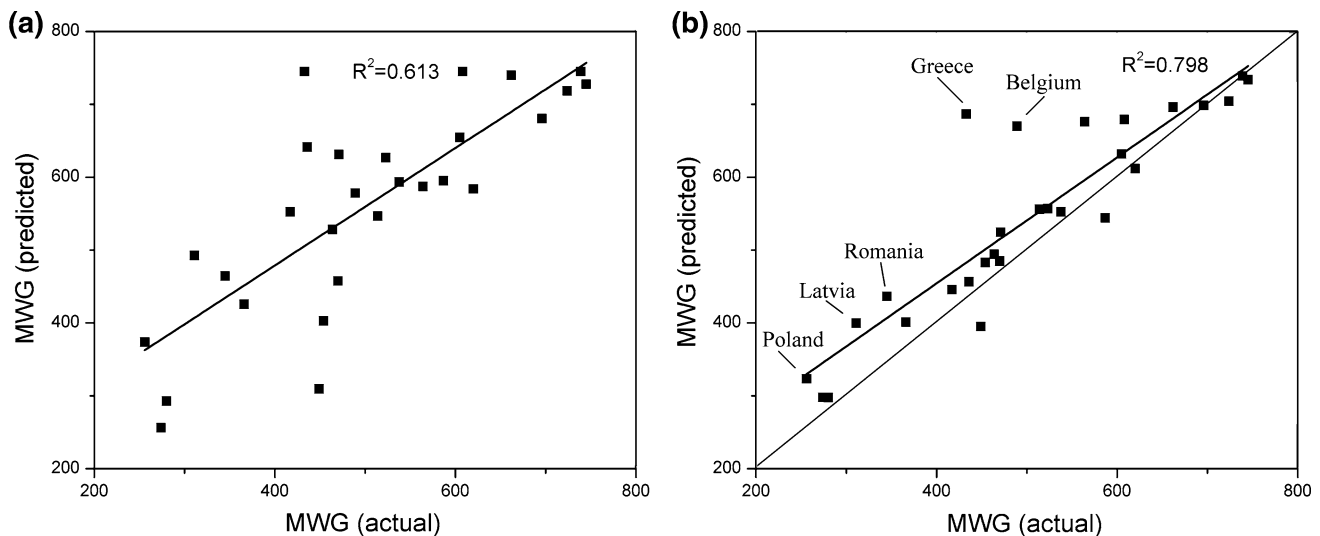


Fig. 6 Comparison of actual (measured) data and ANN results for MWG of European countries for year 2004 (validation dataset). **a** BP ANN, **b** GRNN

In the case of Hungary, although there was an improvement in the quality of data from the year 2000 due to the weighing of waste in treatment sites (Eurostat 2010d); the data for the training and validation years were not typical because of the implementation of the EU waste list in these years. No data for MWG in Hungary for the years 2001–2003 are available at the European Environmental Agency website (European Environment Agency 2010).

Of the European countries used for creating the ANN models, Bulgaria was especially selected for analysis because of its relatively lower level of development and its similarity to Serbia (geographical location, population,

level of development, etc.), for which the model was tested as well. Additional inputs for the years 2003–2007, which for Bulgaria were available from Eurostat, were applied to the GRNN model and the results are presented in Fig. 7.

The GRNN model gives values that correspond closely to the actual values of MWG for Bulgaria, with a maximum relative error of 17 % (year 2006). The landfill site in Sofia was closed between October 2005 and December 2007, which led to a temporary storage amounting to 2.5 % of the total MWG for 2005 and 10 % for 2006 and 2007. These estimated amounts are included in the figures for MWG and caused a drop in municipal waste landfilled in 2006 and 2007 (Eurostat 2010d). Considering all these

Table 5 Example of validation dataset for 2005: actual values of municipal waste and ANN predictions made by the models

Region/country	GDP Compared to GDP (EU27)	DMC kg per capita	RP € per kg	MWG (kg per capita)				
				Actual	BP ANN	RelErr (%)	GRNN	RelErr (%)
EU (27 countries)	1.00	15,746 ^a	1.30 ^b	517	577	11.79	525	1.52
EU (15 countries)	1.19	19,483 ^a	1.55 ^c	558	601	7.81	572	2.51
Belgium	1.28	18,262 ^a	1.43 ^c	482	594	23.36	610	26.50
Bulgaria	0.12	15,213	0.15	475 ^c	600	26.47	500	5.26
Czech Republic	0.44	18,622	0.39	289	347	20.17	273	5.42
Denmark	1.70	27,961	1.22	737	729	0.96	665	9.77
Germany	1.21	15,726	1.64	564	624	10.72	516	8.51
Estonia	0.37	22,645	0.29	436	318	26.90	406	6.88
Ireland	1.74	32,218	1.04	740	759	2.57	698	5.68
Greece	0.78 ^d	17,306	0.88	438	652	48.91	662	51.09
Spain	0.93	19,993	0.86	597	759	27.14	645	8.04
France	1.22	13,579	1.84	532	666	25.25	528	0.75
Italy	1.08	14,230	1.49	542	550	1.53	574	5.90
Cyprus	0.80	30,047	0.52	739	724	2.00	709	4.06
Latvia	0.25	10,531	0.52	310	461	48.81	444	43.33
Lithuania	0.27	9,886	0.53	376	460	22.28	287	23.57
Hungary	0.39	16,437	0.39	460	305	33.70	340	26.08
Austria	1.32	20,629	1.33	620	594	4.24	567	8.47
Poland	0.28	14,240	0.40	319 ^c	355	11.37	295	7.57
Portugal	0.63	17,180	0.71	446	641	43.66	434	2.60
Romania	0.16	15,442	0.16	377 ^c	350	7.05	500	32.62
Slovenia	0.64	18,792	0.68	423	561	32.51	460	8.79
Slovakia	0.32	12,545	0.41	289	289	0.00	430	48.83
Finland	1.33	39,173	0.73	479	547	14.29	459	4.18
Sweden	1.45	18,319	1.83	482	577	19.68	633	31.33
United Kingdom	1.35	11,652	2.58	585	717	22.53	600	2.56
Norway	2.34	20,986	2.11	759	732	3.62	635	16.36
Switzerland	1.79	12,333	3.16	663	486	26.75	658	0.75

Bold values indicate MWG predictions with relative error greater than 10 % and they also represent results for countries for which the quality of data causes the deviation between the actual data and predicted values given by the GRNN model

^a Estimated data (Eurostat 2010a)

^b Estimated data (Eurostat 2010c)

^c Estimated data (Eurostat 2010d)

^d Estimated data (Eurostat 2010b)

Table 6 Percentage of model predictions with relative error less than 10 % for the validation dataset

Model	Year		
	2003 (%)	2004 (%)	2005 (%)
RelErr <10 % (BP ANN)	57	43	32
RelErr <10 % (GRNN)	71	68	68

factors, it can be concluded that the GRNN model provided satisfactory predictions of MWG for Bulgaria as a developing country.

As with Bulgaria, the available input data for Serbia for the period 2006–2009 was entered into the ANN and the output was compared with the actual MWG. It should be noted that a difference between Serbia and most other European countries is that there have been no measured/ reported actual data for MWG for Serbia (SEPA 2010), and as such the values used in this study are estimates made by

SEPA, which introduces some uncertainty into the analysis of the results.

To make estimations of MWG in Serbia, SEPA measured the amount of waste generated in ten municipalities of Serbia for a period of 7 days several times a year. In these selected municipalities, the number of measurements during the year was not uniform (SEPA 2010). The results of this study suggest that MWG in the ten municipalities selected by SEPA can be used to make satisfactory estimations of MWG in the Republic of Serbia.

The GRNN model gave satisfactory predictions for the years 2006, 2007 and 2009 with relative errors below 10 %; for the year 2008 the relative error was 12 % (Table 7). As can be seen from Table 7, in the period from 2006 to 2008, there was an increase of MWG in Serbia by 50 %. Such a large jump of MWG cannot be justified solely from consumption in Serbia and can be explained chiefly by improved data collection by local waste

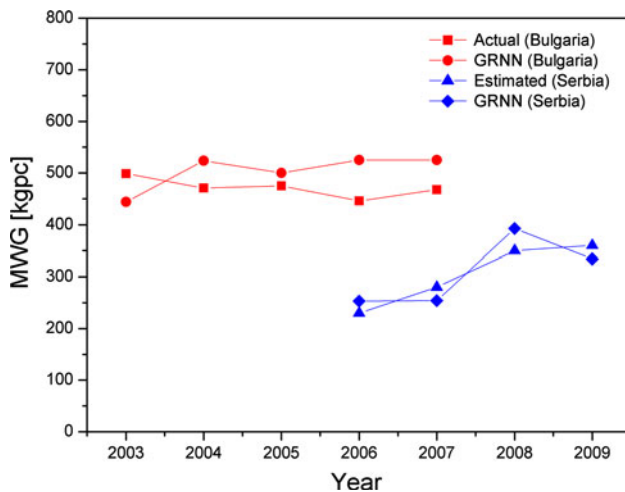


Fig. 7 Actual and predicted values of MWG by the GRNN model for Bulgaria and Serbia

Table 7 Estimated MWG values, GRNN prediction and relative error of estimated and predicted MWG values for Serbia

Year	2006	2007	2008	2009
Estimated MWG values (kgpc)	233	280	350	360
GRNN predictions (kgpc)	253	254	393	334
Relative error (%)	8.33	-9.53	12.22	-7.22

management services. A new Waste Management Law passed in 2009 should contribute to improving the quality of data submitted to SEPA by local waste management services (SEPA 2009), which most probably contributed to a decrease of the relative error in 2009.

Conclusions

The performance of two types of ANN architectures, BP and GRNN, for modeling MWG were compared. GDP, DMC and resource productivity were used as input parameters, while MWG was the output parameter. Data from European countries was used for model training and validation.

Despite the fact that both models were trained and tested with the same datasets, the GRNN model proved to be significantly better than the more traditional BP model. First, it needed a much shorter training time, less than a second, while the training time of BP models with the same training sets lasted for over 100 min. Also, the GRNN model achieved better results in terms of correlation of the predicted values with measured values in the validation dataset. Finally, the results given by GRNN showed considerably higher stability, even in longer time series. Based

on the agreement of GRNN model predictions with measured values, it can be concluded that the model can provide good prediction of MWG for countries at different economic levels, including developing economies such as Bulgaria and Serbia.

Like Serbia, many countries and regions lack the necessary data on which they could implement strategies for improvement of MSWMS. Based on the results obtained in this study, it can be concluded that ANN models can be applied to modeling MWG based on economic, industrial, demographic, etc., parameters that are monitored continuously. By using country performance indicators as an input, the developed model can be used to determine various environmental parameters and their consequential impact on the environment.

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