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RESEARCH ARTICLE

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Predictive model for municipal waste generation using artificial neural networks—Case study City of Zagreb, Croatia

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Summary
The European Union's environmental legislation related to environmental protection, already implemented in the national legislation of the Republic of Croatia, aims to introduce a system of integrated and sustainable waste management. Within such a system, it is of utmost importance to have a better estimate of the amount of municipal waste generated, which directly influences future planning in the waste management sector. The aim of this research was to develop and optimize models for the estimation of generated municipal waste by application of methodology using neural network models, and taking into account the socio-economic impact as well as the inputs regarding the actual waste management trends.
In this paper, an artificial neural network models were used to predict the municipal waste generation in Zagreb, Croatia. The standardized socio-economic and waste management variables were chosen to encompass 2013 to 2016 period. Moreover, the test prediction of the observed data was performed for 2017. Developed models sufficiently predicted the quantities of different municipal waste fractions and in that sense can contribute to better planning of upcoming waste management systems that will be sustainable and in order to meet the European Union commitments.

KEYWORDS
modelling, neural networks, sustainability, waste management

1 | INTRODUCTION

The European Union (EU) waste management policy aims to reduce the environmental and health impacts of waste and improve current resource recovery. Reduction of municipal waste generation can result in a number of environmental, economic, and social benefits, such as reduction in pollution of water and soil, reduction of greenhouse gas emissions, and loss of valuable materials.[1]

The improvement of current waste management practice is one of the main challenges for most cities in Croatia, mainly due to various legal obligations related to waste management at national or European level. Some of them are reduction of waste generation and disposal, increase of separately collected waste fractions, and recycling rates. The waste management process is highly legally regulated where different waste fractions are being tracked from collection until the final treatment. This usually results in significantly large amount of data (types of waste fractions, waste producers, collection frequency, treatment plants, etc.).[2]

For the purpose of defining the municipal waste generation process, it is necessary to apply models and software solutions that can analyse waste streams and quantities, as well as the data on different parameters in selected area: population, economic activity, salaries, etc. On the basis of these data, it is very important to have accurate and standardized historical tracking of input data.[3]

In some papers,[4] authors have concluded that municipal waste generation assessment should take into consideration many indicators and activities that are related to waste management, such as socio-economic parameters (demographic development, economic trends, etc.) as factors which have direct impact on waste generation.

Certain studies[5,6] have shown that one of the most important factors for the future plans in the waste management sector should be an accurate analysis of the current waste streams, as well as a more precise assessment of future generation of municipal waste. Some authors,[7,8] are also using data on a monthly basis for the number of inhabitants, household income, and quantities of municipal waste in order to predict future waste generation, and on this basis, they develop a nonlinear model using an artificial neural network (ANN). In the investigation performed by Vu et al,[9] a nonlinear autoregressive ANN model of waste prediction coupled with a geographic information data was proposed, by which the waste collection route was optimized, according to truck route time, distance, and air emissions. Similar numerical approach was used in a study conducted by Vu et al,[10]in which the lag times relating to variables were investigated in order to more precisely predict municipal yard waste generation using machine learning approaches. The used variables were climatic and socioeconomic variables, which were used to develop yard waste models. ANN models were developed using the time lagged variables for a different number of weeks. In the work presented by Oliveira et al,[11]an ANN model using genetic algorithms was presented in order to estimate the annual amount of separately collected household packaging waste. A total of 10 variables affecting the amount of separately collected packaging waste were identified and used in this ANN model. These variables were related to the level of education of the population, the size and level of urbanization of the municipality, social aspects related to poverty and economic power, and factors intrinsic to the waste collection service. In certain cases, the authors[11] even go a step further and analyse the influence of additional parameters on waste generation, such as density of population, education, and employment.

The aim of this research was to develop and optimize models for estimation of municipal waste generation using neural networks taking into account various socio-economic and waste management indicators in the City of Zagreb as input variables.

This approach resulted in the development of the tool that reflects the waste management trends in the City of Zagreb for the period of 2013 to 2016, which also enables analysis of the already generated waste amounts in order to predict future waste generation and avoid overcapacity planning of the waste treatment facilities.

2 | WASTE MANAGEMENT IN EU AND CROATIA

All of the EU directives have already been implemented in the national Croatian legislation with the aim of introducing an integrated and sustainable waste management system where waste fractions will be treated as a potential resource rather than a problem. The concept of a circular economy is based on the goals of achieving economic development within the context of resources depletion and growing environmental protection constraints. Furthermore, European countries increasingly state that the circular economy approach is a political priority as well.

One of the central pillars of the circular economy is the return of potential waste material back to the economy and the reduction of waste landfilling. This approach has an additional value due to the fact that recycling of material is done through the process that reduces the impact on the environment compared with using virgin materials.

European and national legislations state that the valuable waste fractions must be collected and treated separately in order to allow its reuse or recycling. The legal obligation of municipalities is to organize system for separate collection of different waste fractions, such as paper, biowaste, metals, plastics glass, and textiles. The collection of these waste fractions has been mostly done through the door-to-door system or bring collection points.

Numerous cities in Croatia are facing serious problems with the management of municipal waste due to the existing system, which has proved to be ineffective and strongly depending of the landfilling, and where national secondary raw material market is still at its beginning. One of the main reasons for this is the generally undeveloped waste separation system and the lack of facilities for suitable processing and sorting of collected waste.

Legal framework[12] in Croatia defines the priority of waste management with a primary focus on waste prevention and recycling afterwards. Also, it restricts the disposal of certain waste fractions, such as biodegradable waste and sets an obligation for its separate collection in order to produce compost or energy through anaerobic degradation.[13]

In line with EU action plans for waste management sector,[14,15] some of the goals to be achieved are general reduction in waste generation per capita, recycling and reuse of waste at the maximum feasible rate, the gradual decrease in waste landfilling, and incineration of waste that cannot be recycled. These proposals define ambitious plans to increase the recycling of municipal solid waste and exclude landfilling of all materials that can be recycled by 2025.

The acceptation of circular economy approach will result in the reduction of total waste amounts, where the key EU objectives in the future are recycling 65% of municipal waste by 2030, recycling 75% of packaging waste by 2030, and a ban for disposal of separately collected waste. These goals must be in the future implemented into Croatian legislation as well.

The further development of sustainable waste management will result in a significant reduction of waste disposal and its negative impact on the environment. Also, it will boost the reuse and recycling of the useful materials that are part of the municipal solid waste (paper, plastics, textiles, etc.) and contribute to the implementation of waste management hierarchy.

According to official data,[16] the amount of municipal waste generated in Croatia before 2005 was largely based on estimates. From 2006 onwards, the quantities are determined on the basis of the data reported by the legally obligated entities (municipalities and waste management companies), with an additional estimation of the data regarding municipalities not covered by the organized waste collection and the municipalities whose data are not being reported. The increase in the total amount of municipal waste was noticed in 2008, followed by decreasing quantities of waste until 2010.

The methodology for monitoring the waste generation in Croatia is from 2013 fully compatible with the EU standard and has included the waste streams from additional producers (small companies, service providers, etc.). This has resulted in a slight increase of the total amount of municipal solid waste produced in 2013 compared with 2012. In 2014, the amount of generated waste has decreased to the values of 2010, when the generated municipal waste was approximately 1.6 million tons, which was certainly influenced by various national socio-economic trends and the economic crisis that followed. The total amount of generated municipal waste produced in Croatia for the period of 1995 to 2016 is presented in the Figure 1.

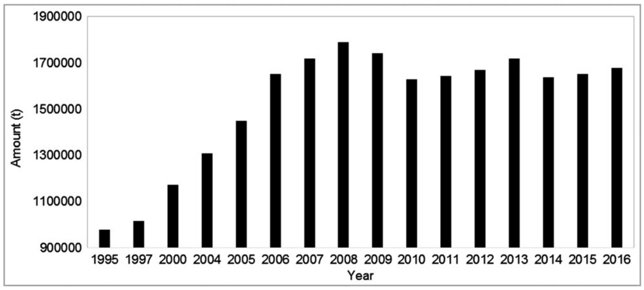

FIGURE 1 Landfilled waste amounts in the Republic of Croatia[16]

Regarding the various legal obligations that Croatia has to fulfil, one of the most demanding is necessary reduction of the municipal waste disposal and limitation for the landfilling of the biodegradable waste. Specifically, the goal regarding restrictions towards the biodegradable waste landfilling is regulated by the law,[12] which states the maximum quantities of biodegradable waste that can be annually landfilled compared with the amounts of biodegradable waste produced in 1997. Trends related to the landfilling of biodegradable waste are shown in Figure 2. The allowed amounts are 75% or 567.131 tonnes by 31 December 2013, 50% or 378 088 tonnes by 31 December 2016, and 35% or 264 661 tonnes by 31 December 2020. It can be expected that the targets regarding the decrease of the biodegradable waste landfilling will not be met.

The presented fluctuations of the waste generation in Figure 1 is a proof that waste management sector through its main activity (waste collection) may vary due to the impact of different external factor, presumably not the ones linked with the actual waste management practice. Also, presented legal obligations in the Figure 2 are confirming the necessity for application of more advanced tools for waste generation assessment in order to sufficiently organize future activities in this sector. This is especially important having in mind energy potential of the municipal waste and its valuable fractions.[2]

3 | ENERGY UTILIZATION

Due to the fact that sustainability criteria must be implemented in the waste management, besides the recycling and material recovery energy utilization of waste is another way to recover valuable resources. It is a vital part of a sustainable waste management chain and is fully complementary to recycling.

There are numerous possibilities that enable useful exploitation of waste fractions for energy production,

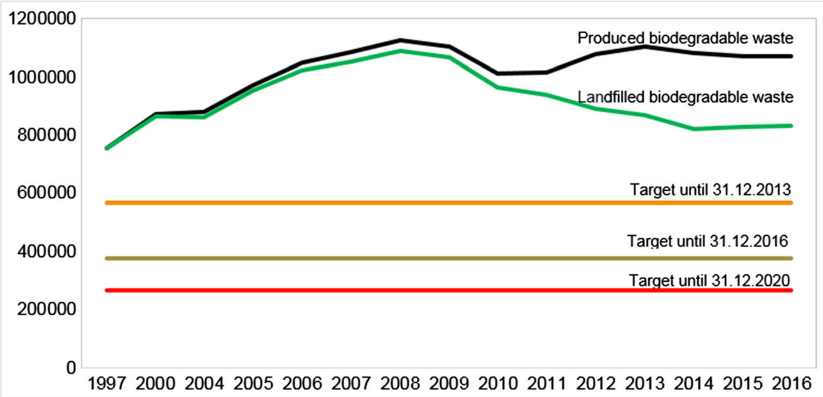

FIGURE 2 Management of the biodegradable waste in the Republic of Croatia[16] [Colour figure can be viewed at wileyonlinelibrary.com]

and one of the options is anaerobic digestion and biogas production of biodegradable waste. Such a treatment of biowaste has two positive effects: landfilling prevention and production of an important energy source with potentially multiple usage.

Main advantage of anaerobic digestion compared with the composting is energy production through the optimal utilization of biogas from biowaste, upgraded to natural gas (methane) quality, and its utilization as a biofuel. In addition, it is possible to directly connect upgraded biogas to the natural gas network. Likewise, there is option of using biogas in cogeneration units, producing electricity and heat, but it presumes the consumption of heat throughout the year.[2]

4 | CASE STUDY: CITY OF ZAGREB

The City of Zagreb, as the capital of Croatia, is a unit of local self-government with the status of regional self-government. It covers area of more than 641.32 km^2 and consists of 17 districts. According to the 2011 census, Zagreb has about 790 000 inhabitants.[17] Organized collection of municipal solid waste covers all residents of the City, most of them live in residential buildings (about 70%) and the rest in residential houses. The produced municipal waste is mainly collected through the system of curb-side collection from bins located on the public area. Collection of waste is organized twice a week for mixed solid waste and twice a month for recyclables (paper, plastics, and metals). The average amount of municipal waste produced in the City of Zagreb is 386 kg/capita with recycling rate between 15 and 20%. The total amount of mixed municipal waste that was landfilled in the period 2007-2014 is shown in the Figure 3.

The main fraction of the municipal solid waste is biodegradable stream: paper and cardboard, kitchen waste, green waste, wood, etc. (Figure 4), and therefore,

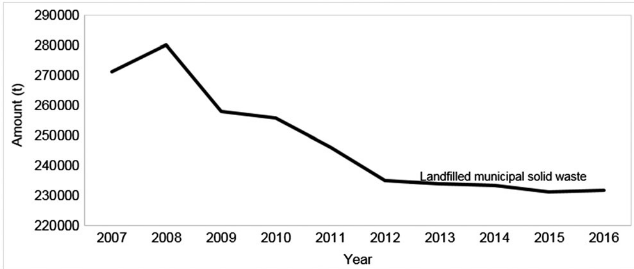

FIGURE 3 Total amount of landfilled municipal waste in the City of Zagreb[16]

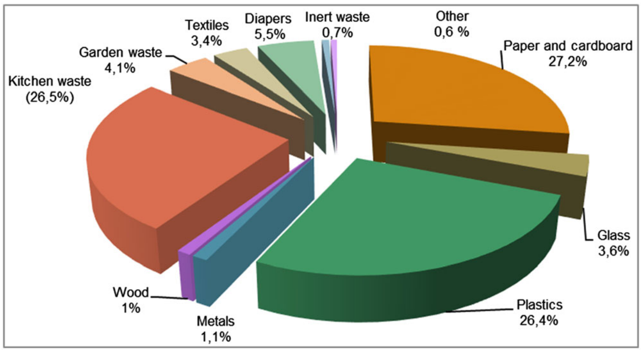

FIGURE 4 Composition of the mixed municipal waste in the City of Zagreb in 2017[18] [Colour figure can be viewed at wileyonlinelibrary.com]

sustainable management of biodegradable waste presents one of the most important challenges in the City of Zagreb. Usually, the most efficient way regarding the increase of collected recyclables is the introduction of separate collection, especially of the paper/cardboard and biowaste. The total amount of treated biodegradable waste in the City of Zagreb is presented in the Figure 5.

Since the quantities of collected recyclables are low, current waste management system in the City of Zagreb needs to be significantly improved in order to be more resource efficient and to align current practice with the priorities in the waste management sector. The main goal

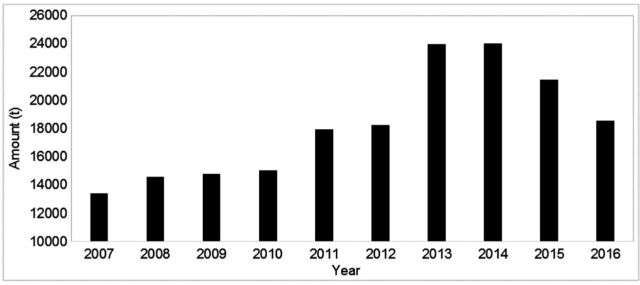

FIGURE 5 Annual amount of treated biowaste at the composting plant in the City of Zagreb[19]

should be reduction of landfilling and steering towards the efficient recycling of household waste.

The existing waste management system as a whole should be redefined in accordance with legal obligations, and in that sense, there is a need to increase the amount of separately collected waste. It is also necessary to improve the current waste collection infrastructure through an increased number of waste disposal bins and containers for paper, plastics, textiles, glass, etc.

Nevertheless, construction of treatment facilities in the city for collected recyclables (sorting facilities, biogas plants, etc.) is necessary. This necessity is strongly supported by a fact that over a 30% of generated municipal waste in the city is of biodegradable origin (Figure 5), and in that sense is an argument in favour of energy utilization of biowaste. Treated biowaste and fermented residue from anaerobic digestion has no odour and, thus, its disposal does not cause this kind of problems for the population in the vicinity of the plant.

5 | MATERIALS AND METHODS

5.1 | Data collection

In this paper, models for estimation of municipal waste generation in the City of Zagreb for the period 2013-2016 have been developed. The used input data were divided into two groups: socio-economic and waste management indicators.

For the purpose of this research, data source that was for socio-economic indicators in the period 2013 to 2016 was the *Statistical Yearbooks of the City of Zagreb*.[20] Statistical data of these yearbooks cover the most important areas of social and economic activities, as well as geographical, meteorological, and basic data about the City of Zagreb. These official statistics are a standardized source of data with 25 chapters and more than 1000 related indicators. Some of the covered socio-economic indicators are number of households, construction activities, employment/unemployment, education, salaries, corporations and economy, transport and goods exchange, vital statistics (birth, deaths, and marriages), and number of tourists.

In this paper, as a data source regarding the waste management indicators was official, reports provided by waste collection company (Zagreb holding-branch Cistoca) were used.[19] Since the collection of the waste is organized in accordance with the legal requirements,[21] analysed waste management variables were municipal and industrial waste fractions, recycling yards, total number of bins, etc. Total quantities of different waste streams are divided to different groups according to waste producers (municipal and industrial waste fractions) and the place of disposal (public area and recycling yards), with additional subgroups based on different waste fractions: mixed municipal waste, biodegradable waste, packaging of paper and cardboard, plastics, etc.

5.2 | Statistical analysis

Previously described waste management situation in the City of Zagreb emphasized the fact that predictions of the future waste amounts are challenging. Besides the actual number of people, economic situation and consumption have a strong impact on total waste generation. It can be easily noticed in the Figure 1, when due to the economic crisis (2009 and 2010), the amount of generated waste was in decline. This is the reason for development and comparison of three ANN models in order to analyse broader impact of different indicators to waste generation.

The ANN models were used for estimation of the main effect of the input variables on network outputs. To that purpose, ANN1/1, ANN1/2, and ANN2 models were developed.

In order to predict socio-economic variables in 2017, it was necessary to create a model based on the known data (2013-2016). The first step was to create the ANN1/1 model, which should be capable to predict the socio-economic data, based upon the available data: month and year variables. The predicted socio-economic variables were accurately calculated, and compared with measured values of these variables. The creation of ANN1/1 model was not necessary to predict the socio-economic variables between 2013 and 2016 (they were already known), but to predict the socio-economic indicators for 2017 and afterwards to predict municipal waste indicators for 2017 (using ANN2 model).

ANN1/1 model predicted three socio-economic indicators, while ANN1/2 model predicted 14 waste management indicators, based on year and month as an accessory variable to relate the socio-economic and the municipal waste indicators.

In ANN2 model, three socio-economic indicators calculated in ANN1/1 model were used to evaluate 14 waste management indicators.

The collected data were presented using descriptive statistics tables. The analysis and mathematical modelling was performed using STATISTICA 10.0.[22]

The symbols used for the presentation of socio-economic indicators in this paper have following meaning: total number of tourists (TOR), total number of households (TNH), and salaries (SAL), while the employed waste management indicators are glass packaging waste (GPW), paper and cardboard waste (PCW), biodegradable waste (BDW), municipal solid waste (MSW), bulky waste (BLW), total quantities of all waste fractions (TWF), biodegradable waste from kitchen and canteen (BWK), biodegradable waste (BDW), total industrial waste (TIP), mixture of concrete waste (MCW), waste electronic equipment (hazardous waste) (EEH), waste electronic equipment (EEE), total number of containers (TNC), and total number of containers for recyclable waste (TCR).

The independent variables used for modelling of ANN1/1 and ANN1/2 models were year (2013-2016) and month (1-12), while the output variables were the socio-economic (ANN1/1) and waste management (ANN1/2) variables for the period from 2013 to 2016. ANN1/1 model was also used to predict the socio-economic indicators in 2017, according to a model developed using the data for a period between 2013 and 2016.

The input model variables used for modelling of ANN2 were the socio-economic indicators: TOR, TNH, and SAL, for a period from 2013 to 2016. The ANN2 model calculated the waste management indicators (GPW, PCW, BDW, BDW, MSW, BLW, TWF, BWK, BDW, TIP, MCW, EEH, EEE, TNC, and TCR), based on the socio-economic indicators from 2013 to 2016, and also predicts the waste management indicators in 2017. The schemes of both models are presented in Figure 6.

5.3 | ANN modelling

A multilayer perceptron (MLP) model, which consisted of three layers (input, hidden, and output) was used for model establishment. This model has been proven as quite capable of approximating nonlinear functions.[23] Before the calculation, both input and output data were normalized in order to improve the behaviour of the ANN. During this iterative process, input data were repeatedly presented to the network.[24,25] Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm was used as an iterative method for solving unconstrained nonlinear optimization problems in ANN modelling.

The experimental database for ANN was randomly divided into: training, cross-validation, and testing data (with 60%, 20%, and 20% of experimental data, respectively). The training data set was used for the learning cycle of ANN and also for evaluation of the optimal number of neurons in the hidden layer and the weight coefficient of each neuron in the network. It was assumed that successful training was achieved when learning and cross-validation curves approached zero.

The coefficients associated with the hidden layer (weights and biases) were grouped in matrices W_1 and B_1. Similarly, coefficients associated with the output layer were grouped in matrices W_2 and B_2. It is possible to represent the neural network by using matrix notation (Y is the matrix of the output variables; f_1 and f_2 are transfer functions in the hidden and output layers, respectively; and X is the matrix of input variables)[26]:

$$Y = f_1(W_2 \cdot f_2(W_1 \cdot X + B_1) + B_2). \tag{1}$$

The weights (elements of matrices W_1 and W_2) were determined during the ANN learning cycle, which updated them using optimization procedures to minimize the error between network and experimental outputs,[25,27] according to the sum of squares (SOS) and BFGS algorithm, used to speed up and stabilize convergence.[28] The coefficients of determination were used as parameters to check the zperformance of the obtained ANN model.

5.4 | The accuracy of the models

The numerical verification of the developed models was tested using coefficient of determination (r^2), reduced

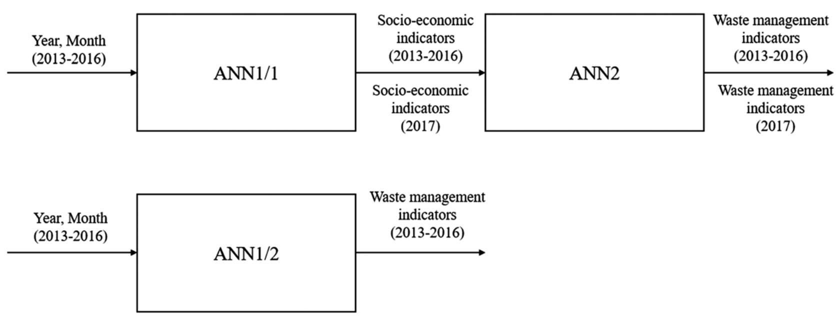

FIGURE 6 Artificial neural network models scheme of ANN1 and ANN2

chi-square (χ^2), mean bias error (MBE), root-mean-square error (RMSE), and mean percentage error (MPE). These commonly used parameters can be calculated as follows[29]:

$$\chi^2 = \frac{\sum_{i=1}^{N}\left(x_{\exp,i} - x_{\mathrm{pre},i}\right)^2}{N-n},\ \mathrm{RMSE} = \left[\frac{1}{N}\cdot\sum_{i=1}^{N}\left(x_{\mathrm{pre},i} - x_{\exp,i}\right)^2\right]^{1/2},$$

$$\mathrm{MBE} = \frac{1}{N}\cdot\sum_{i=1}^{N}\left(x_{\mathrm{pre},i} - x_{\exp,i}\right),\ \mathrm{MPE} = \frac{100}{N}\cdot\sum_{i=1}^{N}\left(\frac{\left|x_{\mathrm{pre},i} - x_{\exp,i}\right|}{x_{\exp,i}}\right), \tag{2}$$

where $x_{\exp,i}$ stands for the measured values and $x_{\mathrm{pre},i}$ are the predicted values calculated by the model for these measurements. N and n are the number of observations and constants, respectively.

6 | RESULTS AND DISCUSSION

Summary statistics of the socio-economic and waste management data for the City of Zagreb obtained from year 2013 to 2016 are presented in Table 1.

TABLE 1 Descriptive statistics of the collected data

	Input Variables			Output Variables					
	TOR	TNH	SAL	GPW	PCW	BDW	MSW	BLW	TWF
Average	85 000	360 000	867	33	42	44	18 000	310	21 000
SD	31 000	5 900	115	52	53	64	1 400	310	2 700
Min	34 000	360 000	840	2.3	3.5	2.70	15 000	0.0	16 000
Max	140 000	370 000	907	150	220	450	21 000	1200	28 000
Skewness	-0.021	-0.179	1.688	1.300	1.739	5.545	-0.100	1.506	1.125
Kurtosis	-1.187	-1.725	4.209	-0.153	2.107	34.531	0.525	1.140	1.558
Output variables									
	BWK	BDW	TIP	MCW	EEH	EEE	TNC	TCR	
Average	11	240	550	260	25	30	110 000	9 700	
SD	4.9	85	120	160	10	18	7 300	2 300	
Min	4.6	68	310	23	7.5	6.3	97 000	4 100	
Max	21	450	830	650	48	72	120 000	12 000	
Skewness	0.353	0.075	0.150	0.579	0.193	0.607	-0.305	-1.494	
Kurtosis	-1.138	0.305	-0.168	-0.459	-0.768	-0.647	-1.273	1.187	

Abbreviations: BDW, biodegradable waste, tonne; BLW, bulky waste, tonne; BWK, biodegradable waste from kitchen and canteen, tonne; EEE, waste electronic equipment, tonne; EEH, waste electronic equipment (hazardous waste), tonne; GPW, glass packaging waste, tonne; MCW, mixture of concrete waste, tonne; MSW, municipal solid waste, tonne; PCW, paper and cardboard waste, tonne; SAL, salaries (euro); TCR total number of containers for recyclable waste; TIP, total industrial waste, tonne; TNC, total number of containers; TNH, total number of households; TOR, total number of tourists; TWF, total quantities of all waste fractions, tonne.

TABLE 2 Artificial neural network model summary (performance and errors), for training, testing, and validation cycles for ANN1/1 and ANN1/2 models

Model	Network Name	Performance Train.	Test	Valid.	Error Train.	Test	Valid.	Training Algorithm	Error Function	Hidden Activation	Output Activation
ANN1/1	MLP 2-9-3	0.997	0.994	0.994	0.011	0.012	0.009	BFGS 227	SOS	Tanh	Identity
ANN1/2	MLP 2-7-14	0.710	0.637	0.623	1.800	5.167	3.795	BFGS 106	SOS	Exponential	Exponential

Abbreviations: Test., testing; Train., training cycle; Valid., validation.

TABLE 3 Artificial neural network model summary (performance and errors), for training, testing, and validation cycles for ANN2 model

Model	Network Name	Performance Train.	Test	Valid.	Error Train.	Test	Valid.	Training Algorithm	Error Function	Hidden Activation	Output Activation
ANN2	MLP 3-6-14	0.826	0.342	0.740	$8.9\cdot10^{11}$	$2.3\cdot10^{12}$	$3.7\cdot10^{12}$	BFGS 188	SOS	Exponential	Identity

Abbreviations: Test., testing; Train., training cycle; Valid., validation.

TABLE 4 Coefficients of determination (r^2) between experimentally measured and ANN1/2 outputs, during train, test, and validation steps

Cycle	GPW	PCW	BDW	MSW	BLW	TWF	BWK	BDW	TIP	MCW	EEH	EEE	TNC	TCR
Train	0.679	0.866	0.643	0.860	0.808	0.881	0.949	0.732	0.671	0.956	0.908	0.929	0.967	0.954
Test	0.548	0.837	0.435	0.579	0.914	0.508	0.800	0.640	0.827	0.979	0.906	0.971	0.981	0.913
Valid	0.340	0.770	0.651	0.915	0.983	0.969	0.983	0.920	0.641	0.987	0.987	0.954	0.990	0.936

Abbreviations: BDW, biodegradable waste; BLW, bulky waste; BWK, biodegradable waste from kitchen and canteen; EEE, waste electronic equipment; EEH, waste electronic equipment (hazardous waste); GPW, glass packaging waste; MCW, mixture of concrete waste; MSW, municipal solid waste; PCW, paper and cardboard waste; TNC, total number of containers; TIP, total industrial waste; TCR, total number of containers for recyclable waste; TWF, total quantities of all waste fractions.

TABLE 5 Coefficients of determination (r^2) between experimentally measured and ANN2 outputs, during train, test, and validation steps

Cycle	GPW	PCW	BDW	MSW	BLW	TWF	BWK	BDW	TIP	MCW	EEH	EEE	TNC	TCR
Train	0.894	0.934	0.602	0.660	0.928	0.759	0.919	0.584	0.837	0.946	0.921	0.889	0.920	0.845
Test	0.218	0.007	0.075	0.096	0.212	0.645	0.835	0.220	0.331	0.917	0.788	0.629	0.991	0.836
Valid	0.852	0.848	0.912	0.547	0.822	0.692	0.856	0.749	0.112	0.846	0.788	0.782	0.956	0.943

Abbreviations: BDW, biodegradable waste; BLW, bulky waste; BWK, biodegradable waste from kitchen and canteen; EEE, waste electronic equipment; EEH, waste electronic equipment (hazardous waste); GPW, glass packaging waste; MCW, mixture of concrete waste; MSW, municipal solid waste; PCW, paper and cardboard waste; TNC, total number of containers; TIP, total industrial waste; TCR, total number of containers for recyclable waste; TWF, total quantities of all waste fractions.

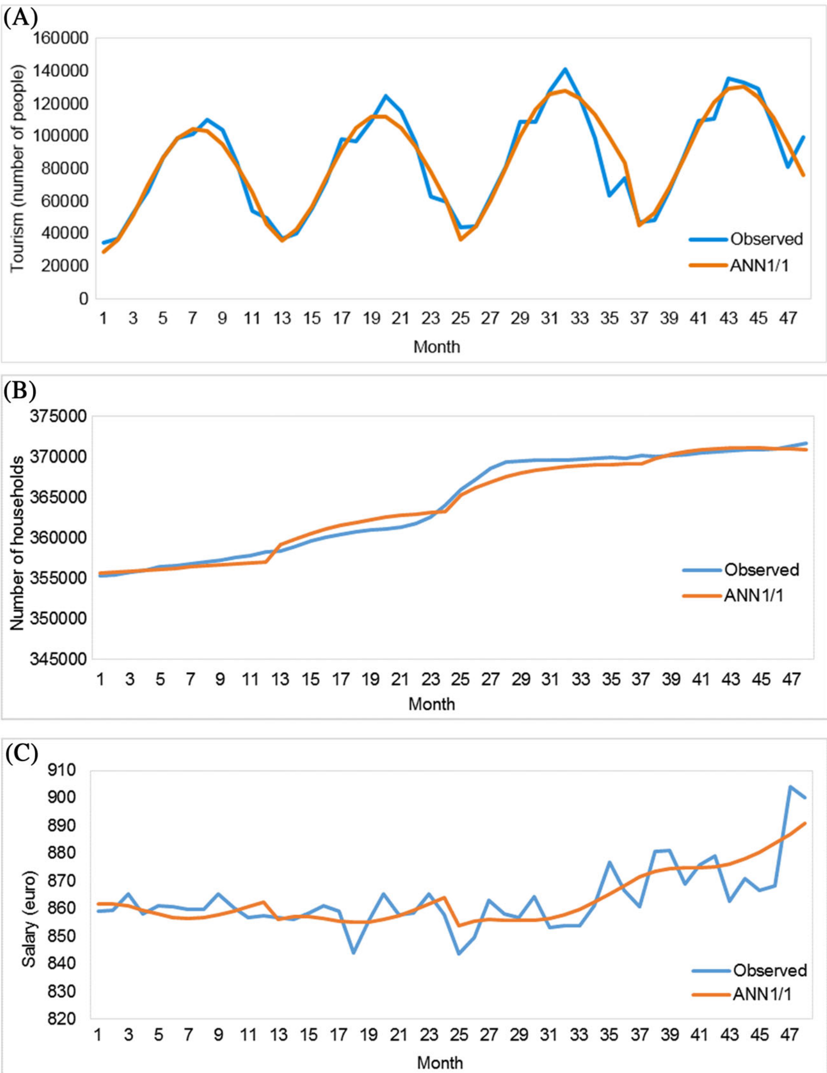

FIGURE 7 Observed socio-economic variables and ANN1/1 model presented values of A, total number of tourists, B, total number of households, and C, salaries for period of 2013-2016 [Colour figure can be viewed at wileyonlinelibrary.com]

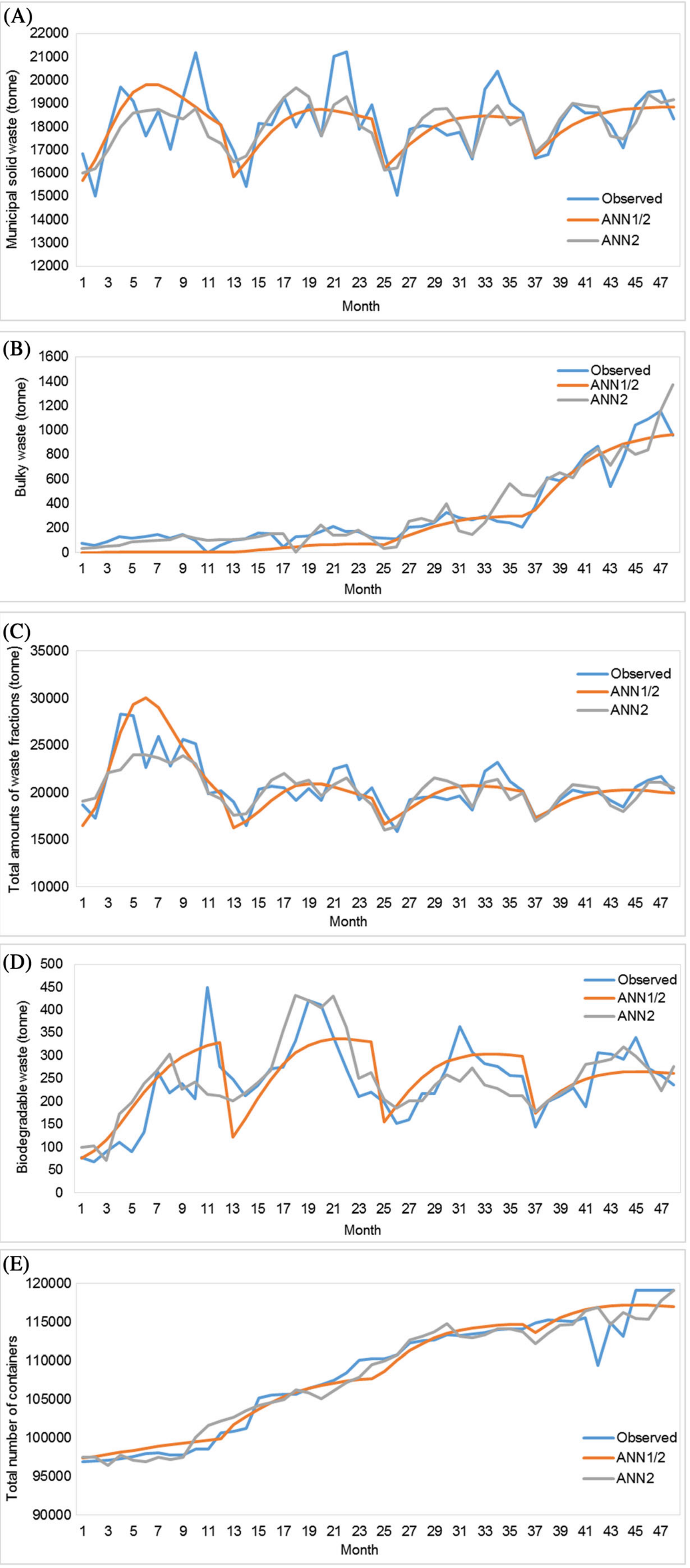

FIGURE 8 Observed waste management variables, ANN1/2 and ANN2 model presented values of A, municipal solid waste, B, bulky waste, C, total quantities of all waste fractions, D, biodegradable waste, and E, total number of containers for period 2013-2016 [Colour figure can be viewed at wileyonlinelibrary.com]

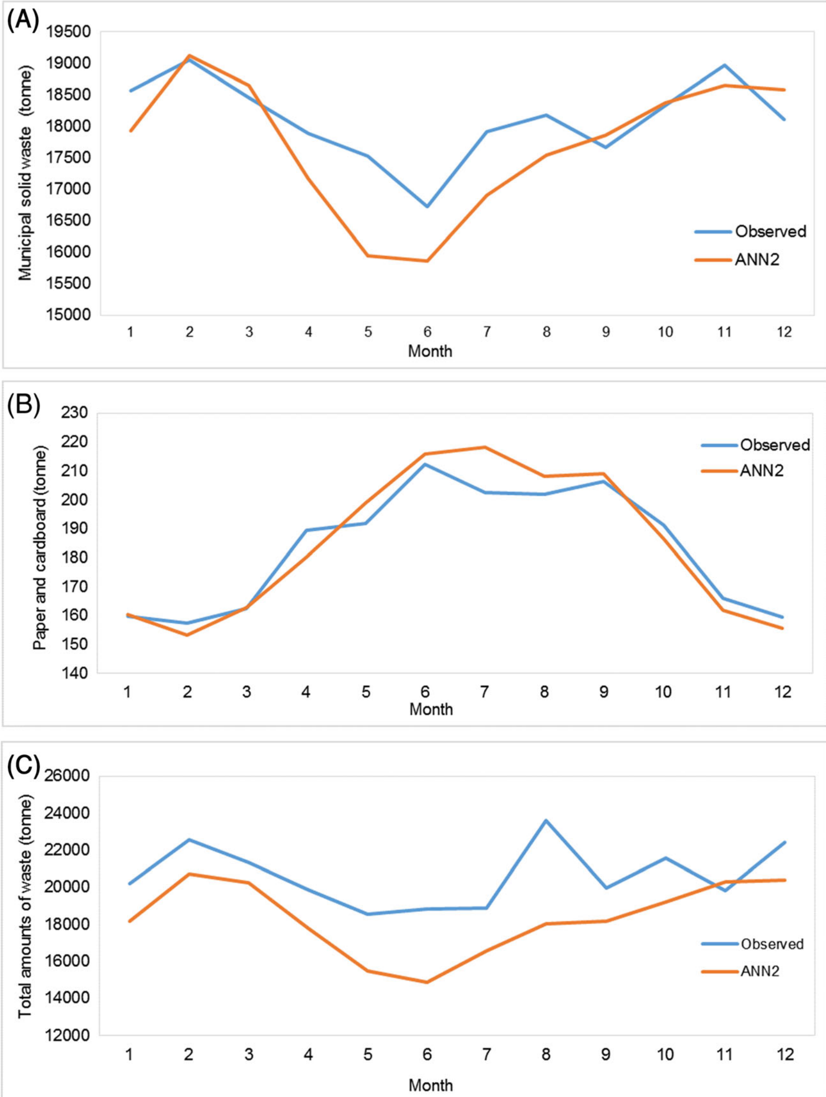

FIGURE 9 Observed waste management indicators and ANN2 model predicted values of A, municipal solid waste, B, paper and cardboard waste, C, total quantities of all waste fractions, D, waste electronic equipment (hazardous waste), E, mixture of concrete waste, and F, total number of containers for 2017 [Colour figure can be viewed at wileyonlinelibrary.com]

6.1 | ANN model

The developed optimal neural network models showed a good generalization capability for the experimental data and could be used to accurately calculate the socio-economic and waste management variables for the City of Zagreb in the period of 2013 to 2016.

According to ANN performance of the socio-economic indicators, the optimal number of neurons in the hidden layer for ANN1/1 was 9 (network MLP 2-9-3) to obtain high values of r^2 (overall 0.997 for ANN1/1 during the training period) and low values of *SOS* (0.012). For ANN2 it was eight neurons in the hidden layer (network MLP 2-8-3) and obtained overall value of r^2 was 0.944.

Regarding the waste management indicators, the optimal number of neurons in the hidden layer for ANN1/2 network was 7 (network MLP 2-7-14) with r^2 value of 0,710, and for ANN2 was 6 (network MLP 3-6-14) with r^2 equals to 0.826 obtained for ANN during the training period. The main characteristics of the developed ANN1/1 and ANN1/2 models are presented in the Table 2, while ANN2 performance is presented in Table 3. Performance terms in the tables represent the coefficients of determination, while error terms indicate the lack of data for the ANN model.

The goodness of fit between experimental measurements and model-calculated outputs, for waste collection data for Zagreb, Croatia, from year 2013 to 2016 represented as ANN performance (sum of r^2 between

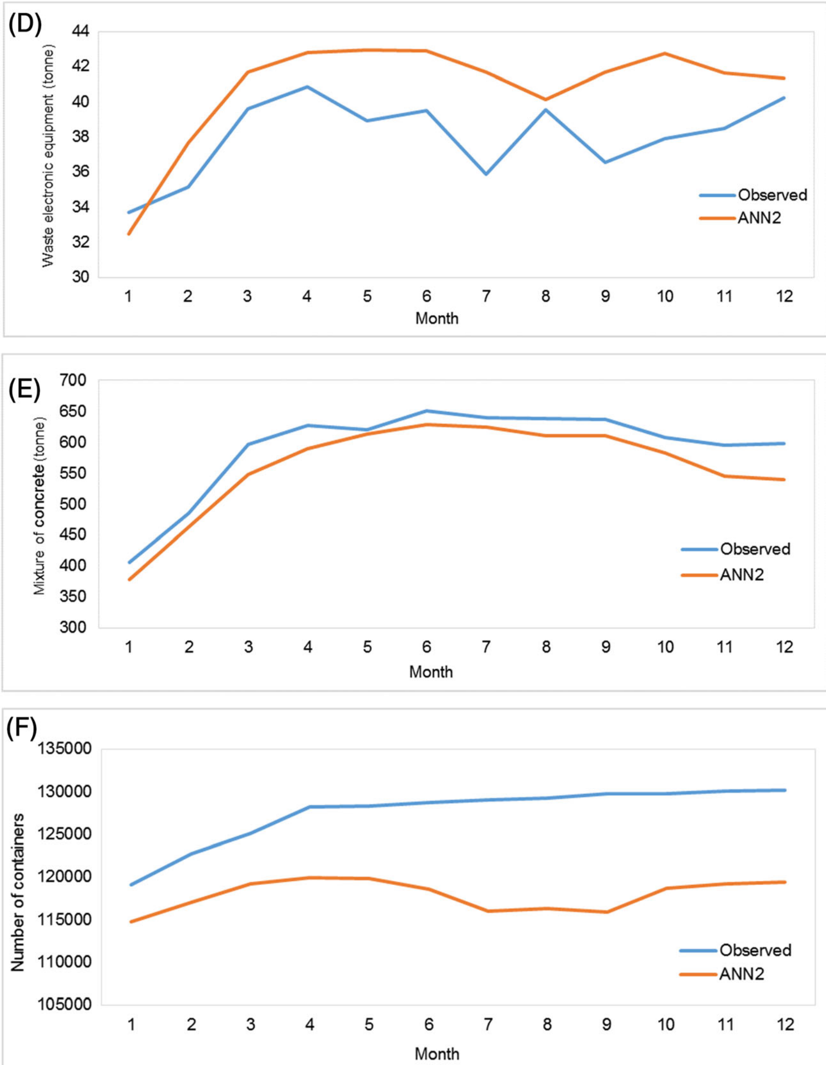

FIGURE 9 Continued.

measured and calculated outputs), during training, testing, and validation steps, and for ANN1/2 and ANN2 is shown in Tables 4 and 5.

As mentioned before, for the period of 2013 to 2016, the ANN1/1 and ANN1/2 models presented three socio-economic and 14 waste management indicators, while ANN2 model predicted 14 waste management indicators for 2017, based upon the socio-economic parameters calculated in ANN1/1 model. ANN1/1 model represented socio-economic indicators (TOR, TNH, and SAL) for 2013-2016, reasonably well for a broad range of the process variables, as seen in Figure 7, where the experimentally measured (observed) values were presented. Figure 8 presents measured (observed) values of MSW, BLW, TWF, BDW, and TNC, compared with calculated using values of these variables using ANN1/2 and ANN2 models.

For the developed models, the predicted values were very close to the obtained values in most cases. *SOS* obtained with ANN model was of the same order of magnitude as experimental errors for output variables reported in the literature.[25] The ANN models are complex (ANN1/1 with 57, ANN1/2 with 140, and ANN2 with 122 weights-biases) because of the high nonlinearity of the developed system.[25,30]

The r^2 values between experimental measurements and ANN1/2 model outputs GPW, PCW, BDW, MSW, BLW, TWF, BWK, BDW, TIP, MCW, EEH, EEE, TNC, and TNR were 0.679, 0.866, 0.643, 0.860, 0.808, 0.881, 0.949, 0.732, 0.671, 0.956, 0.908, 0.929, 0.967, and 0.954 and for ANN2/2 were0.894; 0.934; 0.602; 0.660; 0.928; 0.759; 0.919; 0.584; 0.837; 0.946; 0.921; 0.889; 0.920, and 0.845, respectively, during the training period.

The quality of the model fit was tested and presented in supplement materials (Tables 1–3). The ANN1/2 and ANN2 models had an insignificant lack of fit tests, which means the models satisfactorily predict the municipal waste amounts in the City of Zagreb for 2017. A high r^2 is indicative that the variation was accounted for and that the data fitted the proposed model satisfactorily.[31-33]

6.2 | Future prediction capabilities

In this research, an attempt was made to predict the values of waste collection parameters GPW, PCW, BDW, MSW, BLW, TWF, BWK, BDW, TIP, MCW, EEH, EEE, TNC, and TCR for 2017 year (using ANN2 model), based on the predicted socio-economic values in 2017 (TOR, TNH, and SAL). The results of these models are presented in Figure 9.

The quality of the model prediction for 2017 year was tested and the results are presented in Table 9 (part of supplement material).

7 | CONCLUSION

The aim of this paper was to develop models for estimation of municipal waste generation in urban areas through the usage of different socio-economic and waste management indicators. For this purpose, standardized data of the City of Zagreb were used for the period of 2013 to 2016.

This research presented ANN models of three socio-economic and 14 waste management trends in the City of Zagreb. The optimal number of neurons for developed models was eight for ANN1/1, nine for ANN2, and seven for ANN1/2, respectively. Models have complex structure with total number of weight biases in the range of 57 (ANN1/1) to 122 (ANN2). The obtained overall r^2 values were 0.997 for ANN1/1, 0.710 for ANN2, and 0.826 ANN1/2, which confirmed sufficient prediction capabilities of models.

This study indicate that socio-economic variables such as total number of households, number of tourists, and salaries could be efficiently used for prediction of different waste fractions, such as paper and cardboard, municipal solid waste, and bulky waste.

Taking into account that a limited amount of data was used in the present work to obtain the ANN model, and considering that this model proved to be capable to achieve a sufficiently good representation and prediction of data, it is expected to be very useful in practice.

The developed ANN models are easy to use, applicable on global scale, fast, and with sufficient precision. Its application should also be further improved with the addition of new data over time and therefore could improve current activities by the municipalities in the waste management sector.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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