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PREDICTING THE FUTURE TRENDS OF EUROPEAN AND NATIONAL BENCH-MARKS IN THE MANAGEMENT OF BIODEGRADABLE MUNICIPAL WASTE USING ARTIFICIAL NEURAL NETWORKS

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Abstract

This research employs Artificial Neural Networks (ANN) to develop predictive models for biodegradable municipal waste at both European and national levels. Leveraging socio-demographic and economic data spanning 25 years across 17 European Union (EU) countries, the models aim to forecast biodegradable waste generation over a five-year period. The primary objective is to examine the influence of socio-demographic and economic factors on waste generation. According to the study's findings, it is anticipated that by 2025, the 17 EU countries will produce approximately 67.4 million tons of mixed municipal waste (MMW), 14.7 million tons of municipal paper and cardboard waste (PCW), 6.4 million tons of municipal wood waste (WW), and approximately 0.6 million tons of municipal textile waste (TW). This substantial volume underscores the pressing need for robust infrastructure covering collection, processing, recycling, and disposal mechanisms. The ANN model demonstrated impressive predictive capabilities for MMW, PCW, WW, and TW. Test predictions spanning 2020 to 2025 revealed R2 values ranging between 0.965 and 0.998 during the training phase for the output variables.

Key words: *artificial intelligence, Europe, reduction of municipal waste, quantity estimation, waste generation, waste management.*

INTRODUCTION

Biodegradable waste is any waste that undergoes anaerobic or aerobic decomposition (Council Directive 1999/31/EZ; Vis, 2017). Depending on local conditions, climate, energy source, degree of industrialization and consumer habits regarding food and drink consumption, between 60-70% of municipal waste consists of biodegradable municipal waste (food waste, green waste, paper, and cardboard wastes, etc.) (Garćia et al., 2005; Vergara et al., 2012). Proper management of biodegradable waste is particularly important, considering that the amount of greenhouse gases from waste depends on how the waste is treated. Greenhouse gases are released by disposing of biodegradable waste in landfills and its decomposition (Kujawska et al., 2016; Eurostat, 2023). In 2019, waste management was the 4th largest source of greenhouse gases in the EU and accounted for about 3.3% of greenhouse gases when distributed by sectors (European Parliament. Infographic: Greenhouse gas emissions by country and sector, 2022). Therefore, biodegradable waste (which includes bio-waste) is the key source of greenhouse gas emissions from landfills (EEA, 2018). The above is not surprising if you consider the fact that between 118 and 138 million tons of bio-waste is generated in the EU annually, while only less than 40% is currently recycled into useful products (ECN, 2022). There are also calculations that show that the USA annually disposes almost 300 million tons of organic waste in landfills (Themelis, 2022). Given that large amounts of biodegradable waste are still disposed of in landfills, and keeping in mind that this practice has a negative impact on the environment, it is necessary to urgently apply alternative methods of managing this type of waste (Garćia et al., 2005). With the aim of preserving the environment, great efforts have been invested in environmentally conscious management of biodegradable waste. In November 2021, a global pledge had been signed in Glasgow, in which more than a hundred countries of the world undertake to reduce emissions of the greenhouse gas methane by 30% by 2030 compared to the amount in 2020 (Le Page, 2021). Just by changing the way biodegradable waste is managed, the USA would be well on its way to reducing methane emissions by 30 percent (Themelis, 2022).

To initiate positive changes, this work aims to create a model for predicting the amount of generated waste of four different components of biodegradable municipal waste using ANNs, which could have a practical benefit in achieving a more efficient waste management system. Proper separation of biodegradable waste would set the pre-conditions for further processing with more environmentally friendly methods, such as composting or anaerobic digestion. In this way, the release of greenhouse gases that occur due to the decomposition of organic material in landfills would be reduced (Wei et al., 2017), and compost and digestate could be used in agriculture as quality soil amendments.

Given that, the mechanism of municipal waste generation is a very complex process and there is a connection between socioeconomic factors and the generation of municipal waste, non-linear regression models like ANN show better accuracy than linear ones. Therefore, the use of neural networks in predicting the generation of waste has recently become more frequent (Wu et al., 2020). As an example, Kulisz and Kujawska (2020) used ANNs to predict municipal waste generation in Poland. Data on waste and socioeconomic data of several municipalities were used for the development of mathematical models. In that re-search, ANN had good predictive quality in terms of determining waste production trends, both in the local context and at the national level (Kulisz & Kujawska, 2020).

Building on the success of previous applications where Artificial Neural Networks (ANN) demonstrated effectiveness in waste generation prediction, this research aims to leverage ANN to develop models for estimating the generation of mixed municipal waste (MMW), municipal paper and cardboard waste (PCW), municipal wood waste (WW), and municipal textile waste (TW). The focus extends to both national and EU levels, encompassing the analysis of various socio-demographic characteristics, economic factors, and industrial data across seventeen EU countries.

MATERIALS AND METHODS

ANN modelling

Artificial Neural Networks (ANNs) exhibit a unique capability to process extensive datasets, making them an essential tool for deciphering intricate input-output connections within nonlinear systems (Abdoli et al., 2011; Ribić et al., 2019; Agatonovic-Kustrin & Beresford, 2000; Bunsan et al., 2013). Their broad applicability arises from their proficiency in modelling complex nonlinear relationships (Ghazi Zade & Noori, 2008; Noori et al., 2009; Antanasijević et al., 2013). In this research, an ANN model is employed to predict the generation of mixed municipal waste (MMW), municipal paper and cardboard waste (PCW), municipal wood waste (WW), and municipal textile waste (TW). The analysis encompasses socio-demographic, economic, and industrial data across 17 EU countries: Belgium, Croatia, Czech Republic, Denmark, Estonia, France, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Slovenia, Spain, and Sweden, spanning the period from 1995 to 2019.

The input variables, comprising demographic data, economic progress, number of employed individuals, education level, tourism, and waste, were extracted from the web site of the statistical office of the EU (Eurostat). Eurostat's website was chosen for its provision of high-quality statistics and data from member states, countries outside the EU, and international organizations. The primary criterion for data selection was the availability of data for a specific variable during the period from 1995 to 2019 or for as long as possible. Total annual data for each country was utilized in model development. After collecting and verifying all data, the construction of the ANN commenced. In the end, 28 input variables were used, including: year (YEAR), population

(POP), LE (life expectancy), EL1 (educational attainment level, less than primary, primary and lower secondary education), EL2 (educational attainment level, upper secondary, post-secondary non-tertiary and tertiary education), EL3 (educational attainment level, upper secondary and post-secondary non-tertiary education), ELT (tertiary education), GDP (gross domestic product at market prices), RGDP (real GDP per capita), TFS (total financial sector liabilities, by sub-sectors, non-consolidated), NED (net external debt), NEER (nominal effective exchange rate), DIRE (direct investment in the reporting economy), TEMP (total employees from 15 - 64 years), URAD (unemployment rate), YUR (youth unemployment rate), MENI (median equalized net income), ATAE (arrivals at tourist accommodation establishments), NSTA (nights spent at tourist accommodation establishments), IGS (imports of goods and services), EGS (exports of goods and services), EOPP (exports of oil and petroleum products by partner country), HPI (house price index, deflated), RRMW (recycling rate of municipal waste), DL (disposal - landfill), GMWK (generation of municipal waste, kilograms per capita) and GMWT (generation of municipal waste, thousand tonnes), and CNT (country, as categorical variable).

Based on the collected input data, ANN model was created with the aim of predicting the output results (four fractions of biodegradable municipal waste in thousands of tons) for the period from 1995 to 2019. There were some missing data in the input database, but at this stage, ANN predicts them as well. Given that the goal of the research was to predict the amount of biodegradable municipal waste that will be generated in the near future, it was necessary to predict the input data for the same period. The above was also done using ANNs. It was necessary to create 26 models based on the variable - time (year) and the categorical variable - name of the country. After that, in the initial mathematical model that was created earlier, the input data were replaced by "new", predicted data. These are the same sociodemographic and economic parameters mentioned earlier, but with data for a different period. Based on this data, data for 17 member states of the EU will be obtained for 26 input data and four output data for the period from 2020 to 2025.

The database for creating the ANN was divided into three parts: training (60%), cross-validation (20%), and testing (20%) data. The number of hidden neurons in the ANN model, developed as multilayer perceptron, varied from 5 to 30. The optimization process aimed to minimize the validation error, and training was considered successful when the learning and cross-validation curves reached zero after 100,000 training iterations. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm was employed as a tool for solving unconstrained nonlinear problem in the course of ANN model building. The optimization was based on minimizing the sum of squares (SOS) and accelerating convergence (Taylor, 2006).

The coefficients for the hidden layer were represented by matrices W_1 and B_1, while the coefficients for the output layer were represented by matrices W_2 and B_2 (Ochoa-Martínez & Ayala-Aponte, 2007):

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

where:
- f_1 and f_2 are transfer functions in the hidden and output layers, respectively;
- X is the matrix of input variables.

Global sensitivity analysis

The Yoon interpretation method (Yoon et al., 2017) was applied to determine the relative influence of input data on MMW, PCW, WW and TW, based on the weight coefficients of the developed ANN.

$$RI_{ij}(\%) = \frac{\sum_{k=0}^{n}(w_{ik} \cdot w_{kj})}{\sum_{i=0}^{m}\left|\sum_{k=0}^{n}(w_{ik} \cdot w_{kj})\right|} \cdot 100\% \tag{2}$$

where:
- w - weight coefficient in ANN model;
- i - input variable;
- j - output variable;
- k - hid-den neuron;
- n - number of hidden neurons;
- m - number of inputs.

The accuracy of the model

Numerical verification of the obtained ANN model was tested using the following commonly used parameters (defined in Eq. 3-8): coefficient of determination (R^2), reduced chi-squared (χ^2), mean bias error (*MBE*), root mean square error (*RMSE*), mean percentage error (*MPE*), error sum of squares (*SSE*), and average absolute relative deviation (*AARD*) (Aćimović et al., 2020):

$$\chi^2 = \frac{\sum_{i=1}^{N}(x_{\exp,i} - x_{pre,i})^2}{N-n} \tag{3}$$

$$RMSE = \left[\frac{1}{N}\cdot\sum_{i=1}^{N}(x_{pre,i} - x_{\exp,i})^2\right]^{1/2} \tag{4}$$

$$MBE = \frac{1}{N}\cdot\sum_{i=1}^{N}(x_{pre,i} - x_{\exp,i}) \tag{5}$$

$$MPE = \frac{100}{N}\cdot\sum_{i=1}^{N}\left(\frac{\left|x_{pre,i} - x_{\exp,i}\right|}{x_{\exp,i}}\right) \tag{6}$$

$$SSE = \sum_{i=1}^{N}(x_{pre,i} - x_{\exp,i})^2 \tag{7}$$

$$AARD = \frac{1}{N}\cdot\sum_{i=1}^{N}\left|\frac{x_{exr,i} - x_{pre,i}}{x_{exr,i}}\right| \tag{8}$$

RESULTS AND DISCUSSIONS

Two ANN models were developed for the estimation of the main effect of the input variables on network outputs. ANN1 model was used to predict MMW, PCW, WW, and TW, during 1995 to 2019, based on socio-economic data between 1995 and 2019. The in-put database contained some missing data, and ANN1 model was engaged to predict those as well (Figure 1a). To predict socio-economic variables in 2020-2025, it was necessary to create an ANN model based on the known data (1995-2019). The first step was to create the ANN2 model, which could be capable to predict the socio-economic data in 2020-2025, based upon the available data: known socio-economic data (1995-2019), YEAR and CNT (Figure 1b). To obtain better modelling results, 26 separate ANN models were developed instead of just one model, and this set of models would be titled as ANN2 further in the text. The evaluated socio-economic indicators in 2020-2025 (calculated using ANN2 model) were used as inputs in ANN1 model to evaluate MMW, PCW, WW, and TW, in 2020-2025 (Figure 1c).

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

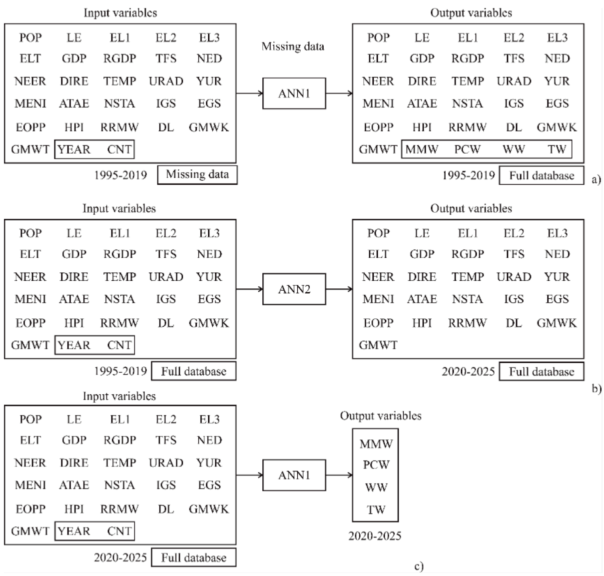

Figure 1. ANN models for prediction of MMW, PCW, WW, and TW, based on socio-economic data

The structure of the ANN, encompassing biases and weight coefficients, as well as the obtained results, is contingent on the initial assumptions of the matrix parameters crucial for building and fitting the ANN to experimental data. Additionally, the behaviour of the ANN model can be influenced by the number of neurons in the hidden layer. To mitigate this concern, each ANN model topology underwent 100,000 runs to eliminate random correlation arising from initial assumptions and the random initialization of weights. According to this approach, the highest R^2 value throughout the training cycle was achieved when employing n hidden neurons to construct the ANN model (Figure 2a).

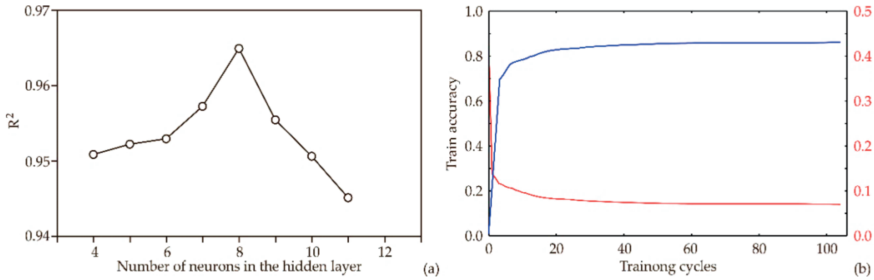

Figure 2. ANN calculation for DIRE variable: (a) The dependence of the R2 value of the number of neurons in the hidden layer in the ANN model; (b) Training results per epoch

Each ANN model underwent training for 100 epochs, and the training results, including train accuracy and error (loss), are illustrated in Figure 2b. Training accuracy exhibited an increase with increments in the number of training cycles until the 70-80th epoch, reaching an almost constant value. The highest train accuracy and lowest train loss were observed for the 70-80th epoch, beyond which a slight increase in train accuracy and a decrease in train loss were noted, indicative of overfitting. Utilizing more than 80 epochs for training could potentially lead to significant overfitting, while 70 epochs proved sufficient to achieve high model accuracy without incurring the risk of overfitting (Figure 2b). The constructed optimal neural network ANN1 model showed promising generalization property for the collected database and could be used to accurately predict the settlement waste: 20 (network MLP 44-20-4) to obtain the highest values of R^2 (during the training cycle, R^2 for output variables (MMW, PCW, WW and TW) were: 0.999; 0.998; 0.997 and 0.998, respectively) The obtained ANN models for predicting the outcome variable were complex corresponding to the in-creased degree of nonlinearity in the data. The estimate of the quality of fit between the collected data and the outputs computed by the model, expressed as the ANN power (sum of R^2 between measured and computed output variables) during the training, testing and validation steps, is explained in Table 1.

Table 1. The "goodness of fit" tests for the formulated ANN model

Output variable	χ^2	*RMSE*	*MBE*	*MPE*	*SSE*	*AARD*	R^2
MMW	$4.3\ 10^4$	$2.1\cdot10^2$	3.5	$1.6\cdot10^1$	$9.4\cdot10^6$	$4.2\cdot10^4$	0.999
PCW	$6.6\cdot10^3$	$8.0\cdot10^1$	1.2	$6.0\cdot10^1$	$1.4\cdot10^6$	$1.5\cdot10^4$	0.997
WW	$1.7\cdot10^3$	$4.1\cdot10^1$	-5.1	$9.2\cdot10^1$	$3.7\cdot10^5$	$1.1\cdot10^4$	0.989
TW	$8.9\cdot10^1$	9.4E+00	1.2	$3.2\cdot10^2$	$1.9\cdot10^4$	$1.1\cdot10^3$	0.992

R^2 - coefficient of determination, χ^2 - reduced chi-squared, *MBE* - mean bias error, *RMSE* - root mean square error, *MPE* - mean percentage error, *SSE* - error sum of squares, and average absolute relative deviation (*AARD*).

The ANN models predicted the data sufficiently well for a wide range of process variables. For all ANN models, the predicted values were very close to the measured values in most cases with respect to the R^2 values. The estimated SOS values of the ANN model were of the same order of magnitude as the errors reported in the literature for output variables (Kollo & von Rosen, 2005), while the lack of fit of the ANN model did not reach a significant level, implying that the model predicted the output variables satisfactorily. An increased R^2 value indicated that the ANN model fitted the data well.

Future prediction capabilities

The main results of this research were the predicted amounts of waste that will be generated in the period from 2020 to 2025. The waste data are presented below (Table 2).

Table 2 shows the amounts of MMW, municipal PCW, WW and TW that were predicted based on mathematical model created using ANN for the period from 2020 to 2025. The estimated amount of MMW in the 17 observed EU countries in 2025 amounts to 67.4 million tons. In the mentioned period (2020-2025) Spain, France and Italy jump in terms of volumes of MMW. In general, from 2020 to 2025, total volumes of MMW for all 17 countries are declining.

The amount of PCW predicted from 2020 to 2025 slightly decreases (around 15 million tons per year) (Table 2). The countries with the largest amounts of PCW are, as with MMW, Italy, France, and Spain. The amounts of municipal WW with an increase in quantities is predicted, and the quantities range between 5.6 and 6.4 million tons per year. The countries with the largest quantities of municipal WW are France and Italy. In the period from 2020 to 2025, the largest amounts of municipal TW will be generated in Italy, France, and Belgium, and the least in Latvia. In the mentioned period, the quantities range between 0.57 and 0.59 million tons per year (Table 2).

According to the results, it is expected that 411.4 million tons of MMW, 90.3 million tons of PCW, 35.9 million tons of WW and 3.5 million tons of TW will be generated between 2020 and 2025.

Table 1. The amount of waste that will be generated from 2020 to 2025 shown in million tons

Year	MMW	PCW	WW	TW
2020	69.8	15.4	5.6	0.6
2021	69.3	15.3	5.8	0.6
2022	68.8	15.1	5.9	0.6
2023	68.3	15.0	6.1	0.6
2024	67.8	14.8	6.2	0.6
2025	67.4	14.7	6.4	0.6

Global sensitivity analysis - Yoon's interpretation method

The influence of 28 input variables on MMPW, PCW, WW and TW was investigated. The results of the research show that all four outputs are positively affected by POP, GDP, MENI, tourism, EOPP, and NED (Figure 3).

According to Kulisz and Kujawska (2020), the smallest member states of the EU have recorded the lowest level of generated waste, which was confirmed in this study. Malta and Luxembourg had the lowest level of generated waste, while France, Italy, Spain have the largest amount of generated waste. Figure 3 also shows how the number of inhabitants has a positive effect on all four observed types of waste with a relative impact of: 3.26% for MMW, 3.77% for municipal PCW, 1.73% for municipal WW and 1.80% for municipal TW, which is in line with previous research (Kulisz & Kujawska, 2020; Badruddin et al., 2002; Gui et al., 2019).

In addition to the local population, visitors and tourists participate in the generation of municipal waste, which can be seen as an additional population in the context of the generation of municipal waste (Arbulú et al., 2015; Grbeš, 2017). The variable indicating overnight stays in tourist accommodation facilities has a positive effect on all four observed types of waste with a relative impact of: 0.59% for MMW, 1.26% for municipal PCW, 0.07% for municipal WW and 3.94% for municipal TW, which is in accordance with the research of Kumar et al. (2011), Mateu-Sbert et al. (2013) and Arbulú et al. (2015).

The results of this study show that GDP has a positive effect on all four observed types of waste, which is in line with previous research by Kusch and Hills (Kusch & Hills, 2017). A similar study was conducted by Namlisa and Komilisa (2019), whose aim was to investigate the potential impact of four socioeconomic indices on waste generation. In their research, EE waste, paper and wood waste, waste oil, small batteries, scrap metals and tires were positively correlated with GDP, indicating that economic growth directly affects waste generation.

MENI positively affects all four observed types of waste with a relative impact of: 1.57% for MMW, 2.02% for municipal PCW, 6.68% for municipal WW and 4.58% for municipal TW.

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The positive impact of net income on waste generation is in accordance with the research of Sabarinah (1997), Bandara et al. (2007), Foday et al. (2012) and Ogwueleka (2013), which show that income has a positive effect on waste generation. In addition, in a study conducted on 39 municipalities in Brazil, a statistically significant linear correlation was observed between income per capita and annual production of municipal waste (R^2 = 0.391) (Namlis & Komilis, 2019).

The global dependence on oil, natural gas and coal, as well as the damage that this dependence causes, is well-known, especially nowadays (Lioudis, 2021). It was shown that the ex-port of oil and oil derivatives has a positive effect on all four types of waste with a relative impact of 2.38% for MMW, 2.30% for municipal PCW, 4.74% for municipal WW and 4.53% for municipal TW. The increase in the price of oil positively affects the economy and standard of living, but also leads to an increase in waste generation.

On the other hand, LE, RGDP, TFS and IGS negatively affect all four types of municipal waste. Other observed factors (such as FDI, annual data on URAD, EGS and education) did not give results from which a single conclusion could be drawn. From the above, it could be seen that the accuracy of predicting the amount of biodegradable waste using ANN really depends on the selection of input socio-demographic, economic and industrial indicators.

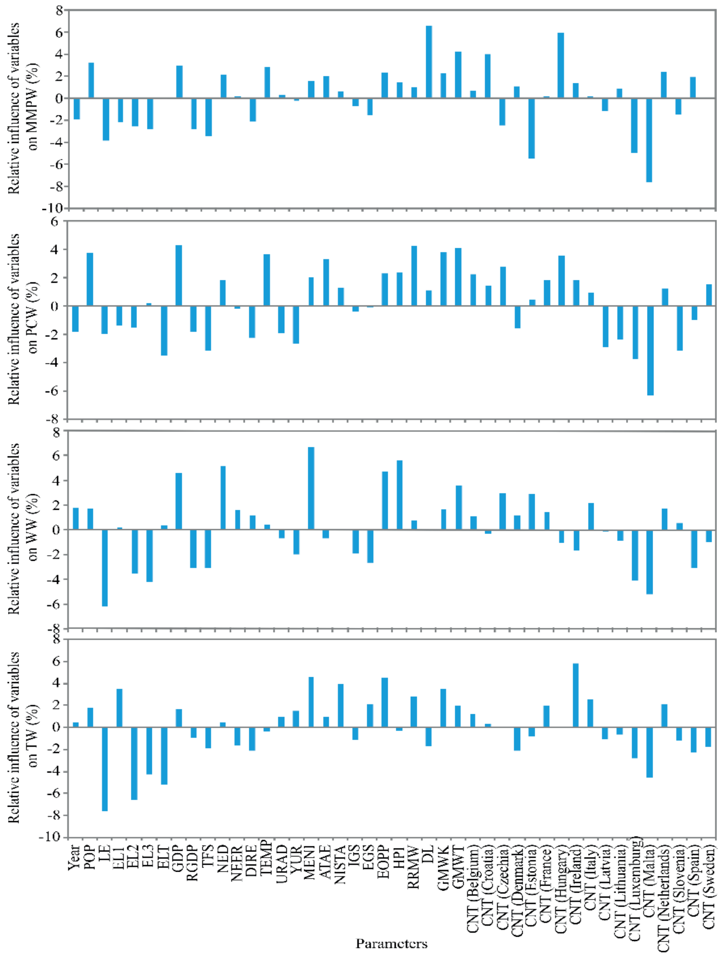

Figure 3. The relative importance of the input variables on MMW, PCW, WW and TW, determined using Yoon interpretation method

Regardless of the satisfactory results and several positive characteristics of ANN, it should be noted that the limitation of this study is the "late" availability of waste data, so future research should upgrade the mathematical model developed in this research with the addition of new data. It could also be assumed that the disease epidemic caused by the coronavirus as well as the war in Ukraine will also affect the amount of waste that will be generated.

CONCLUSIONS

According to the results obtained from this research, it can be expected that in the 17 observed EU countries, the total amount of waste for the four observed fractions (MMW, municipal PCW, WW and TW) in 10 years will increase by approximately 0.5% compared to the data from 2015. It can be also expected that in 2025 in 17 observed EU countries, about 67.4 mil tons of MMW will be generated. The stated amount will include bio-waste that will be unseparated and thrown away as part of MMW. According to the results obtained from this research, it is also expected that in 2025 about 14.7 mil. tons of municipal PCW, 6.4 mil. tons of municipal WW and 0.6 mil. tons of municipal TW will be generated in 17 EU countries. Forecasting the amount of waste generated can help to identify the most appropriate pattern of waste management and at the same time assist decision-makers in updating and modifying legal acts and regulations to enable the transition to a cost-efficient circular economy.

The results also show that all four observed types of municipal waste are positively affected by POP, GDP, TEMP, MENI, tourism, EOPP and NED. On the other hand, LE, RGDP, TFS and IGS negatively affect all four types of municipal waste. From the above, it could be concluded that the accuracy of predicting the amount of biodegradable waste using ANN really depends on the selection of input socio-demographic, economic and industrial indicators. In addition, it can be said that the created mathematical model showed satisfactory properties and possibilities in predicting the amount of MMW, PCW, WW and TW.

In the further research of the topic, it is necessary to expand the research and continue with innovations in the waste management sector if the ambitious goals of the EU to become the first climate-neutral continent in the world by 2050 are to be achieved. In accordance with all the above, the developed mathematical model could serve as a tool to improve waste management so that the organization is more accurate, simpler, and more economical and environmentally friendly. This model would also ensure that waste management changes in parallel with the change in the socio-economic characteristics of society. In future research, the use of new parameters such as family size, eating habits and the impact of waste prevention is encouraged. In addition, it is proposed to expand the research to other countries and other types of waste. Also, it is suggested to repeat the research with more recent data and to investigate the impact of the corona crisis and the war in Ukraine on waste generation. In addition, it is proposed to expand the research to other countries and other types of waste.

AUTHOR CONTRIBUTIONS

Eda Puntarić: conceptualization, investigation, resources, writing - original draft preparation, writing - review and editing.
Lato Pezo: methodology, software, formal analysis, investigation, data curation, writing - original draft preparation, writing - review and editing, visualization.
Željka Zgorelec: validation, supervision.
Jerko Gunjača: validation, supervision.
Dajana Kučić Grgić: validation, supervision.
Neven Voća: conceptualization, methodology, validation, formal analysis, investigation, resources, writing -original draft preparation, writing - review and editing, supervision, project administration, funding acquisition.
All authors have read and agreed to the published version of the manuscript.

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