sustainability

Article

Prediction of the Production of Separated Municipal Solid Waste by Artificial Neural Networks in Croatia and the European Union

Eda Puntarić [1], Lato Pezo [2,*], Željka Zgorelec [3], Jerko Gunjača [3], Dajana Kučić Grgić [4] and Neven Voća [3]

1 Ministry of Environment and Energy, Radnička cesta 80, 10000 Zagreb, Croatia
2 Institute of General and Physical Chemistry, University of Belgrade, Studentski trg, 12/V, 0721 Belgrade, Serbia
3 Faculty of Agriculture, University of Zagreb, Svetošimunska cesta 25, 10000 Zagreb, Croatia
4 Faculty of Chemical Engineering and Technology, Marulićev trg 19, 10000 Zagreb, Croatia
* Correspondence: latopezo@yahoo.co.uk; Tel.: +381-11-3283-185

Abstract: Given that global amounts of waste are growing rapidly, it is extremely important to determine what amount of waste will be generated in the near future. Accurate waste forecasting is also important for planning and designing a sustainable municipal solid waste (MSW) management system. For that reason, there is a need to build a model to predict the amount of MSW generated in the near future. Based on previous research, artificial neural networks (ANN) show better results in predicting waste generation compared to other mathematical models. In this research, an ANN model using the iterative algorithm Broyden–Fletcher–Goldfarb–Shanno (BFGS) for the prediction of MSW fractions, based on the socio-demographic characteristics, economic and industrial data obtained in Croatia and summarized data of the member states of EU (EU-27 from 2020), showed good predictive capabilities. The coefficient of determination during the training cycle for the output variables; household and similar waste (HHS), paper and cardboard waste (PCW), wood waste (WW), textile waste (TW), plastic waste (PW) and glass waste (GW) were 0.993; 0.997; 0.999; 0.997; 0.998; and 0.998, respectively, while reduced chi-square, mean bias error, root mean square error, mean percentage error, average absolute relative deviation and sum of squared errors were found low. In this paper, Yoon′s method of interpretation shows the relationships between socio-demographic data and the amount of generated waste. The results indicate that the lowest level of education shows a negative impact on observed waste-types calculations, with a relative impact between −9.889 and −4.467%. The most pronounced positive impact on the calculation of HHS, PCW, WW, TW, PW and GW was observed for year variable, gross domestic product, exports of goods and services, imports of goods and services, wages and salaries, secondary income, arrivals in collective accommodation establishments, overnight stays in collective accommodation establishments and exports of petroleum and petroleum products to partner countries, with a relative influence of 4.063–7.028; 2828–4851; 5240–6197; 5.308–6.341; 4290–4810; 4533–5805; and 4.345–4.493, respectively. The obtained results indicate that the amount of HHS waste at the EU-27 level in 2025 will decrease by approximately 18% compared to the data from 2018. The quantities of other observed recyclable types of waste will increase by 34% for PCW, 310% for WW, 40% for TW, 276% for PW and about 67% for GW. The amount of waste generated provides the basic information needed to plan, operate and optimize the waste management system. It could also help in the transition to an environmentally friendly and economically profitable circular economy. The model created in this research could also help with the system of separate waste collection, which would lead to more efficient recycling and the achievement of the set goals for recycling 55% of municipal waste by 2025.

Keywords: mathematical modeling; prediction of municipal waste; artificial neural network

check for updates

Citation: Puntarić, E.; Pezo, L.; Zgorelec, Ž.; Gunjača, J.; Kučić Grgić, D.; Voća, N. Prediction of the Production of Separated Municipal Solid Waste by Artificial Neural Networks in Croatia and the European Union. *Sustainability* **2022**, *14*, 10133. https://doi.org/10.3390/su141610133

Academic Editor: Alessio Siciliano

Received: 18 July 2022
Accepted: 14 August 2022
Published: 16 August 2022

1. Introduction

Waste and its production are an inevitable result of human existence. Waste generated in our households, schools, hospitals and businesses is called municipal solid waste (MSW). MSW consists of everyday items that we use and throw away. Discarded products such as packaging, old furniture, clothes, leftover food, newspapers, batteries and more make up MSW. It is very closely linked to people, because people′s behavior determines when a certain item becomes a waste. Therefore, MSW reflects the culture of the people who produce it and has an impact on people′s health and the environment around them. MSW deserves special attention because of its impact on the environment at local, regional and global levels [1–3].

Although MSW in the EU accounts for only between 7% and 10% of total waste generated, it is one of the most difficult categories of waste to manage, often managing more than one third of public sector financial efforts to reduce and control pollution [4,5]. It is estimated that in 2020, 505 kg of MSW were generated per capita in the European Union (EU) [5].

Croatia is the last country to join the EU. In 2020, Croatia generated about 1.7 tons of MSW. There is no official data in the EU-27 yet, but based on forecasts, it is estimated that 225 million tons of MSW were generated at EU-27 level in 2020 [6]. Accurate information on the quantity of waste generation and its composition is essential for planning proper waste management [7]. Environmentally sound, safe and sustainable MSW management should be a top priority in any responsible country or society. Proper and sustainable waste management is particularly important for the EU-27 to achieve targets such as reducing methane emissions by 30% by 2030 and climate neutrality by 2050 [8,9]. To achieve such targets, the European Waste Directive (2008/98/EC) [10] sets goals to contribute to the development of sustainable waste management in the EU. Thus, among other things, the goal is set by which the Member States should ensure the conditions for the reuse and recycling of municipal waste by 2025, with a recycling rate of at least 55%. In Croatia, the recycling rate in 2020 was 34% [11].

Achieving the EU′s targets requires strong momentum and acceleration in the transition to a circular economy and sustainable waste management. The implementation of sustainable management should be guided by the principles of the waste hierarchy. The principles of the waste hierarchy recommend prioritizing from the most desirable waste prevention option at the top, to disposal as the least desirable option at the bottom. In this way, the waste hierarchy helps to shift waste as a problem to waste as a resource and, at the same time minimize the impact of waste on the environment and health to improve resource efficiency [12–18]. In line with the pyramid of the waste hierarchy, the long-term goal of EU policy is to reduce the amount of waste generated and, where unavoidable, to promote it as a resource by achieving higher recycling rates. The model created by this research could help predict the amount of MSW generated. The model created could also help establish better waste management.

Waste generation prediction models have been developed with increasing frequency recently. So far, various models have been used to predict waste generation, such as expert systems, evolutionary programming, artificial neural networks (ANN), multiple linear regression, central composite design and combinations of these tools [19–22]. In this research, ANN will be used because compared to other models, neural networks are relatively insensitive to incomplete information and therefore allow coping with higher degrees of uncertainty. ANN are mathematical models of information processing that function similarly to the human brain and are used to solve artificial intelligence problems. ANN are non-linear tools that use a set of input parameters from which the interconnected elements are calculated, while one or more output parameters represent the final result [22,23].

The management of MSW has become a critical task for municipal cites, based on the increasing daily generation of MSW. The known database records of solid waste generation are trusted and helpful as essential data to avoid environmental pollution, and improve management planning [24–30]. Now, in the era of urbanization and social transformation, not only has the quality of MSW changed, but the quantity has also increased. Excessive generation of solid waste and improper management severely affect environmental and human health [30–37].

The successful planning of waste management system strongly depends on an accurate projection and prediction of MSW quantities, keeping in mind that the future predictions of MSW generation serve as a basis in the development of the existing waste management, infrastructure connections, MSW quantity optimization and sustainable development. Inaccurate predictions could lead to numerous problems, such as inadequate infrastructure for the collection, transportation, landfilling or MSW processing [38–41].

In recent years, mathematical models in the form of ANN has gained popularity, as evidenced by its use in the study of models for predicting the MSW generation. Moreover, the ANN approach is well known for its suitability in estimating nonlinear functions [19–22]. Before computation, the observed database should be normalized to improve the functioning of the ANN. During this recurrent computation, the input data is permanently transmitted to the network [42,43].

The aim of the paper is to show whether it is possible to design a model with a satisfactory degree of accuracy using data on Croatia and pooled data on EU member states, and whether there are differences (and if so, what they are) between these two sets of data. The paper was prompted by the fact that Croatia, as the youngest EU Member State, had to harmonize its national legislation with the EU acquit before joining the EU, including in the area of waste management. Nevertheless, Croatia lags behind other EU Member States in certain issues and segments of waste management and does not comply with certain regulations. On the other hand, 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 an environmentally acceptable and economically cost-efficient circular economy.

The author′s initial hypothesis is that ANN can be a reliable tool that can be used to create a mathematical model for predicting the amount of MSW at the EU and national level. It is also assumed that the accuracy of forecasting quantities depends on the selection of input socio-demographic, economic and industrial indicators, and the results will indicate the parameters that have the greatest impact on waste generation.

2. Materials and Methods

In this paper, ANN is used as a tool to develop a model to predict the generation of household and similar waste (HHS), paper and cardboard waste (PCW), wood waste (WW), textile waste (TW), plastic waste (PW) and glass waste (GW). In this paper, only data for MSW has been used; dataset covered a period of 25 years from 1995 to 2019.

2.1. ANN Modeling

For ANN modeling to predict the parameters of MSW (HHS, PCW, WW, TW, PW and GW), a multilayer perceptron network (MLP) was used, consisting of three layers (Input, Hidden and Output), based on the socio-demographic characteristics, economic and industrial data obtained in Croatia and in the EU countries. The data used were: Year, POP, LE, ELP, ELS, ELSP, ELT, GDP, RGDP, EGS, IGS, EMP, TEMP, WS, MEI, SIP, ATA, NST, EOP, ABH, PRP, RRMW, DISP, RBW, GMWK, GMWT and CNT. Listed socio-demographic and economic parameters were used due to their influence on the amount of waste generation.

For the development of the model, the above data (YEAR, POP, LE, ELP, ELSP, ELT, GDP, RGDP, EGS, IGS, EMP, TEMP, WS, MEI, SIP, ATA, NST, EOP, ABH, PRP, RRMW, DISP, RBW, GMWK, GMWT and CNT) were used in the form of total annual data. The used data set consists of data on Croatia and pooled data on EU Member States. The total dataset covered a total period of 25 years from 1995 to 2019. The data collected were numerical values and categorical variables. The data used to develop the model can be found in the

Supplementary Tables S1 and S2. The data were taken from the official website of the EU Statistical Office.

The collected database for the creation of ANN was stochastically divided into training, cross-validation and testing data (with 60%, 20% and 20% of the data, respectively). A number of different topologies were used, where the number of hidden neurons varied from 5 to 20, and the training process of the network was performed 100,000 times with random initial values of weights and biases. The BFGS algorithm was used as an iterative method to solve the unconstrained nonlinear problems in ANN modeling [44].

The optimization process was performed based on validation error minimization. It was assumed that the training was performed satisfactorily when the learning and cross-validation curves reached zero.

Coefficients related to the hidden layer (weights and biases) were introduced into matrices W_1 and B_1. Similarly, coefficients related to the output layer were described in matrices W_2 and B_2. The neural network model (Y) can be represented using a matrix notation [45]:

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

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

The weight coefficients were resolved and recalculated throughout the ANN learning cycle by applying the rationalization operation to minimize the error between the network and the collected outputs [42,46,47]. During the ANN calculation, sum of squares (SOS) were evaluated and the results of this calculation were used to adjust the weight coefficients in order to accelerate the computation and to consolidate convergence [48]. The performance of the model ANN was examined throughout the calculation using the coefficients of determination.

Statistical investigation of the data has been performed by the Statistica 10 software (Statistica, 2010, Hamburg, Germany).

2.2. Global Sensitivity Analysis

Yoon's interpretation method was used to determine the relative influence of input data on socio-demographic characteristics, economic and industry data [49]. This method was applied 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—hidden neuron, n—number of hidden neurons and m—number of inputs.

2.3. The Accuracy of the Model

Numerical verification of the obtained ANN model was tested using the coefficient of determination (r^2), reduced chi-squared (χ^2), mean bias error (MBE), root mean square error ($RMSE$) and mean percentage error (MPE), average absolute relative deviation ($AARD$) and sum of squared errors (SSE) [50].

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

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

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

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

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

$$AARD = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| \frac{x_{\exp,i} - x_{pre,i}}{x_{\exp,i}} \right| \quad (8)$$

where $x_{\exp,i}$ were experimental values and $x_{pre,i}$ were the model predicted values and N and n are the number of observations and constants, accordingly.

3. Results and Discussion

The constructed optimal neural network model showed promising generalization properties for the collected database and could be used to accurately predict the settlement waste: 7 (network MLP 25-7-6) to obtain the highest values of r^2 (during the training cycle, r^2 for output variables HHS, PCW, WW, TW, PW and GW were 0.999, 1.0, 1.0, 1.0, 0.999 and 0.999, respectively, Table 1).

Table 1. Artificial neural network model summary (performance and errors), for training, testing and validation cycles.

Network Name	Performance *			Error			Training Algorithm	Error Function	Hidden Activation	Output Activation
	Train.	Test.	Valid.	Train.	Test.	Valid.				
MLP 25-7-6	0.999	1.0	1.0	0.0	0.003	0.006	BFGS 85	SOS	Exponential	Identity

* Performance terms represents the coefficients of determination, while error terms specify a lack of data fit for the ANN model.

Table 2 shows the coefficients of matrix W_1 and vector B_1 (exhibited in the bias column), and Table 3 shows the elements of matrix W_2 and vector B_2 (bias) for the hidden layer used for the calculation in Equation (2).

Table 2. Elements of matrix W_1 and vector B_1 (presented in the bias row).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
YEAR	−0.092	−0.080	−0.129	−0.161	−0.197	−0.170	−0.192	0.003	−0.185	−0.069	0.119	0.537	2.282	−0.145
POP	0.559	0.466	0.472	0.503	0.558	0.569	0.527	0.291	0.659	0.562	0.136	0.033	−0.461	0.611
LE	−0.011	−0.020	0.073	0.160	0.120	0.023	0.087	−0.207	0.280	−0.113	−0.160	−0.106	−0.417	0.110
ELP	0.026	−0.272	−0.334	−0.325	−0.201	0.071	−0.019	−0.158	−0.113	0.059	−0.609	−1.114	−2.451	−0.019
ELS	−0.118	0.042	−0.082	−0.528	−0.266	−0.163	−0.172	−0.065	−0.346	−0.180	−0.065	−0.237	−0.169	−0.082
ELSP	−0.089	0.052	−0.248	−0.834	−0.381	−0.113	−0.140	−0.018	−0.604	−0.238	−0.263	−0.915	−1.718	−0.080
ELT	−0.065	−0.101	−0.107	−0.017	−0.078	−0.115	−0.100	−0.232	0.062	0.002	−0.259	0.034	0.382	−0.063
GDP	0.447	0.501	0.521	0.482	0.501	0.525	0.505	0.359	0.646	0.493	0.310	0.254	0.711	0.519
RGDP	0.350	0.227	0.233	0.332	0.317	0.313	0.325	0.138	0.475	0.368	0.083	0.122	0.329	0.347
EGS	0.480	0.454	0.454	0.477	0.487	0.505	0.490	0.400	0.580	0.474	0.391	0.424	1.287	0.549
IGS	0.497	0.427	0.475	0.438	0.473	0.486	0.512	0.394	0.624	0.524	0.415	0.456	1.305	0.569
EMP	0.518	0.462	0.479	0.511	0.515	0.500	0.500	0.334	0.668	0.562	0.187	0.118	−0.028	0.582
TEMP	0.516	0.480	0.495	0.471	0.551	0.516	0.538	0.365	0.677	0.552	0.184	0.167	0.112	0.540
WS	0.533	0.469	0.479	0.486	0.499	0.508	0.498	0.365	0.595	0.479	0.318	0.325	0.832	0.569
MEI	0.166	0.007	0.072	0.241	0.179	0.146	0.161	−0.039	0.354	0.214	−0.073	0.089	0.447	0.201
SIP	0.490	0.456	0.418	0.411	0.444	0.464	0.482	0.334	0.568	0.487	0.302	0.317	0.727	0.533

Table 2. *Cont.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
ATA	0.517	0.449	0.479	0.459	0.491	0.530	0.502	0.408	0.627	0.492	0.349	0.400	1.114	0.535
NST	0.488	0.422	0.423	0.459	0.486	0.456	0.518	0.345	0.615	0.486	0.346	0.377	1.122	0.525
EOP	0.511	0.466	0.444	0.462	0.539	0.576	0.524	0.341	0.646	0.526	0.285	0.208	0.405	0.563
ABH	0.529	0.508	0.505	0.487	0.506	0.552	0.542	0.303	0.693	0.552	0.073	−0.071	−0.731	0.603
PRP	0.524	0.454	0.409	0.483	0.526	0.555	0.509	0.230	0.663	0.521	−0.066	−0.234	−1.547	0.568
RRMW	0.301	0.364	0.269	0.225	0.312	0.340	0.266	0.174	0.369	0.335	−0.019	−0.060	−0.516	0.340
DISP	0.469	0.469	0.424	0.429	0.491	0.513	0.458	0.177	0.632	0.534	−0.117	−0.263	−1.696	0.533
RBW	0.435	0.417	0.429	0.476	0.462	0.400	0.485	0.269	0.618	0.431	0.269	0.242	0.645	0.503
GMWK	−0.134	−0.390	−0.270	−0.004	−0.153	−0.155	−0.178	−0.398	0.077	0.025	−0.553	−0.232	−0.622	−0.180
GMWT	0.558	0.501	0.485	0.503	0.575	0.539	0.506	0.286	0.661	0.540	0.153	0.097	−0.124	0.564
CNT(CRO)	−0.630	−0.683	−0.919	−1.313	−0.961	−0.684	−0.708	−0.563	−1.160	−0.707	−0.782	−1.349	−2.141	−0.699
CNT(EU)	0.527	0.471	0.488	0.481	0.533	0.528	0.522	0.299	0.654	0.541	0.124	−0.002	−0.530	0.605
Bias	−0.128	−0.232	−0.410	−0.846	−0.468	−0.105	−0.185	−0.247	−0.441	−0.154	−0.687	−1.366	−2.637	−0.091

Table 3. Elements of matrix W_2 and vector B_2 (presented in the bias column).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Bias
HHS	0.488	0.505	0.235	0.041	0.080	0.360	0.139	0.521	−0.137	0.573	0.353	0.462	0.548	0.258	−0.859
PCW	0.378	0.352	0.147	−0.027	−0.002	0.268	0.105	0.486	−0.110	0.519	0.232	0.190	0.646	0.273	−0.694
WW	0.282	0.108	−0.180	−0.377	−0.297	0.314	0.052	0.663	−0.522	−0.074	0.459	0.046	4.104	0.065	−0.331
TW	0.305	0.228	0.081	−0.078	−0.066	0.235	0.129	0.328	−0.178	0.414	0.202	0.203	0.673	0.215	−0.518
PW	0.347	0.336	0.171	0.023	0.001	0.231	0.144	0.366	−0.080	0.543	0.221	0.327	0.307	0.305	−0.670
GW	0.316	0.325	0.096	−0.142	−0.079	0.285	0.116	0.472	−0.273	0.444	0.288	0.410	1.281	0.139	−0.590

The obtained ANN model for predicting the outcome variable was complex (230 weights-biases) corresponding to the increased degree of nonlinearity in the data [51,52].

The correctness of the developed model could be measured visually by the scattering of the specific points from the diagonal line in Figure 1. For the model ANN, the expected quality was exceptionally close to the collected data in most cases in terms of r^2 values.

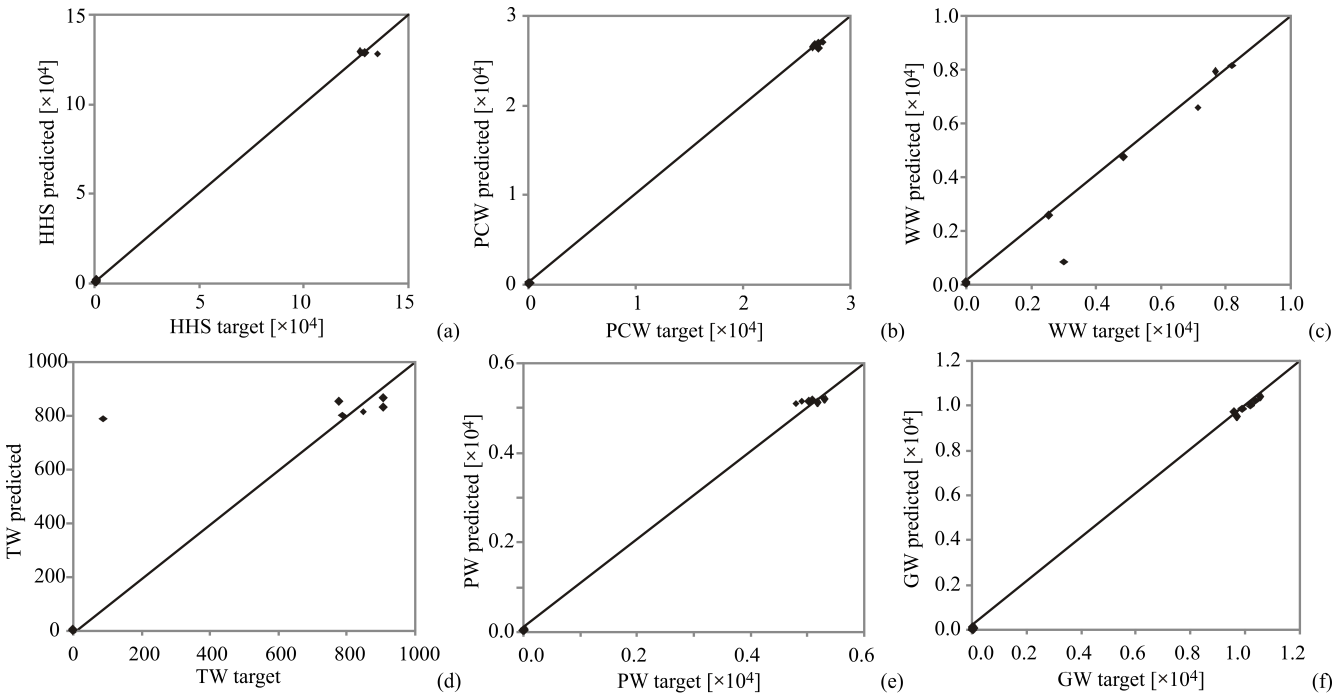

Figure 1. Collected data and data anticipated by the ANN model: (**a**) HHS, (**b**) PCW, (**c**) WW, (**d**) TW, (**e**) PW and (**f**) GW.

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 4.

Table 4. The "goodness-of-fit" tests for the formulated ANN model.

Output Variable	χ^2	RMSE	MBE	MPE	SSE	AARD	r^2
HHS	7.6×10^{-12}	1.2×10^{-6}	1.2×10^{-7}	0.270	2.2×10^{-11}	1.3×10^{-5}	0.993
PCW	2.2×10^{-11}	2.1×10^{-6}	-9.6×10^{-7}	5.167	5.1×10^{-11}	2.6×10^{-5}	0.997
WW	1.1×10^{-11}	1.5×10^{-6}	3.9×10^{-7}	39.469	3.0×10^{-11}	1.4×10^{-5}	0.999
TW	6.8×10^{-14}	1.2×10^{-7}	1.0×10^{-8}	354.591	2.0×10^{-13}	1.2×10^{-6}	0.997
PW	2.8×10^{-12}	7.5×10^{-7}	-3.0×10^{-7}	7.434	7.1×10^{-12}	7.8×10^{-6}	0.998
GW	2.4×10^{-12}	7.0×10^{-7}	-2.8×10^{-7}	4.911	6.1×10^{-12}	7.5×10^{-6}	0.998

The ANN model predicted the data sufficiently well for a wide range of process variables. For the ANN model, 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 [42,47]. 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 [19,20]. The residuals of a fitted model were observed and the corresponding prediction of response was calculated using the ANN regression model. The residuals approximated the random errors that made the relationship between the explanatory variables and the outcome variables, according to a statistical relationship. The residuals appeared to behave randomly, indicating that the model fit the data well (Table 5).

Table 5. The residual analysis for the developed ANN model.

Output Variable	Skew	Kurt	Mean	StDev	Var
HHS	−0.642	2.087	1.2×10^{-7}	1.3×10^{-6}	1.6×10^{-12}
PCW	−1.080	−0.064	-9.6×10^{-7}	1.9×10^{-6}	3.6×10^{-12}
WW	−0.027	1.737	3.9×10^{-7}	1.5×10^{-6}	2.1×10^{-12}
TW	0.394	1.910	1.0×10^{-8}	1.2×10^{-7}	1.4×10^{-14}
PW	−1.300	0.767	-3.0×10^{-7}	7.1×10^{-7}	5.1×10^{-13}
GW	0.102	0.501	-2.8×10^{-7}	6.6×10^{-7}	4.4×10^{-13}

Residual analysis of the developed model was also performed (Table 5). Skewness measures the deviation of the distribution from normal symmetry. If the skewness is significantly different from zero, then the distribution is asymmetric, while normal distributions are perfectly symmetric. Kurtosis measures the "peakedness" of a distribution. If the kurtosis is significantly different from zero, then the distribution is either flatter or more peaked than the normal distribution; the kurtosis of the normal distribution is zero.

Until now, many research projects have been devoted to the study of forecasting the amount of MSW with different mathematical models. Given that the mechanism of MSW generation is a very complex process and that there is a connection between socioeconomic factors and the generation of MSW, nonlinear regression models show greater accuracy than linear ones. Therefore, in recent times, the use of ANN in the prediction of waste generation is increasingly common, which also show better results [16]. Because of the above, no other mathematical models were used in this research, but only ANN. Furthermore, so far, many researchers have successfully applied ANN in MSW forecasting in their local area, and most MSW forecasting models are based on data from a specific region or data for a specific city. Thus, ANNs were also used to estimate the production of MSW in the city of Zagreb [16]. In the aforementioned research, a mathematical model was developed for estimating the production of MSW for the period from 2013 to 2016. The input data used are divided into two groups: socioeconomic indicators and waste management indicators. This study shows how socioeconomic variables such as total number of households, number of tourists and wages can be effectively used to predict different fractions of waste, such as paper and cardboard, mixed municipal waste and bulky waste. The overall r^2 values were between 0.710 and 0.997, which confirmed the predictive capabilities of the model. The authors emphasized that a limited amount of data was used in this work, but the mathematical model nevertheless proved capable of achieving sufficiently good results. Given that waste generation is influenced by a number of parameters and that the conditions and methods of generation of MSW can differ between regions, a small number of studies on forecasting municipal waste on a larger scale have been conducted so far (Wu et al., 2020). The author's desire in this research was to expand the limits of the use of ANN from local and regional areas. Therefore, this work aims to predict the amount of generated MSW in all EU-27 member states.

4. Global Sensitivity Analysis—Yoon's Interpretation Method

The EU has 27 member states, and there are big differences between the members. These differences include economic, demographic, social, economic and other parameters, and there is also a big difference in the amount of municipal waste generated. Variations in the amount of municipal waste generated in the EU member states reflect differences in consumption patterns and economic wealth, but also depend on the way municipal waste is collected and managed. In this work, 27 input parameters were used, which, based on previous research, are known to influence the generation of waste. In this section, the influence of 27 input variables on HHS, PCW, WW, TW, PW and GW was investigated, Figure 2. The CNT variable showed the most negative influence on HHS, PCW, WW, TW, PW and GW calculations, with a relative influence ranging from −10.058 to −8.264%. The ELP variable also showed a negative influence on the HHS, PCW, WW, TW, PW and GW calculations, with a relative influence between −9.889 and −4.467%, Figure 2.

The most pronounced positive influence on HHS, PCW, WW, TW, PW and GW calculation variables was observed for YEAR, GDP, EGS, IGS, WS, SIP, ATA, NST and EOP, with relative significance of: 4.063–7.028; 2.828–4.851; 5.240–6.197; 5.308–6.341; 4.290–4.810; 4.533–5.805; and 4.345–4.493, respectively, Figure 2.

The GDP parameter has the most pronounced positive effect on waste generation. Accordingly, GDP will have a significant impact on increasing waste. This is in line with the research conducted so far by Namlis and Komilis (2019) [27], who also confirmed that the higher the economic growth, the more society spends, and, consequently, the higher the waste production. In conjunction with GDP, other parameters such as EGS, IGS and EOP also have a positive effect on waste generation. This is in line with previously conducted studies that confirmed that the amount of waste generated in a region or country is directly proportional to economic growth and consumption levels [27,28]. Many other studies conducted so far have shown that income has a positive influence on the generation of municipal waste. The positive influence of the parameters WS and SIP can be explained by the fact that residents in low-income countries generally consume fewer goods and generate less waste than in developed countries. This is because daily spending depends on the amount of money available for spending. The more money is available for consumption, the greater the consumer power, and at the same time more (municipal) waste is generated. The obtained results are in line with a study conducted in Brazil where a statistically significant linear correlation was observed between per capita income and annual municipal waste production (r^2 = 0.391) [28].

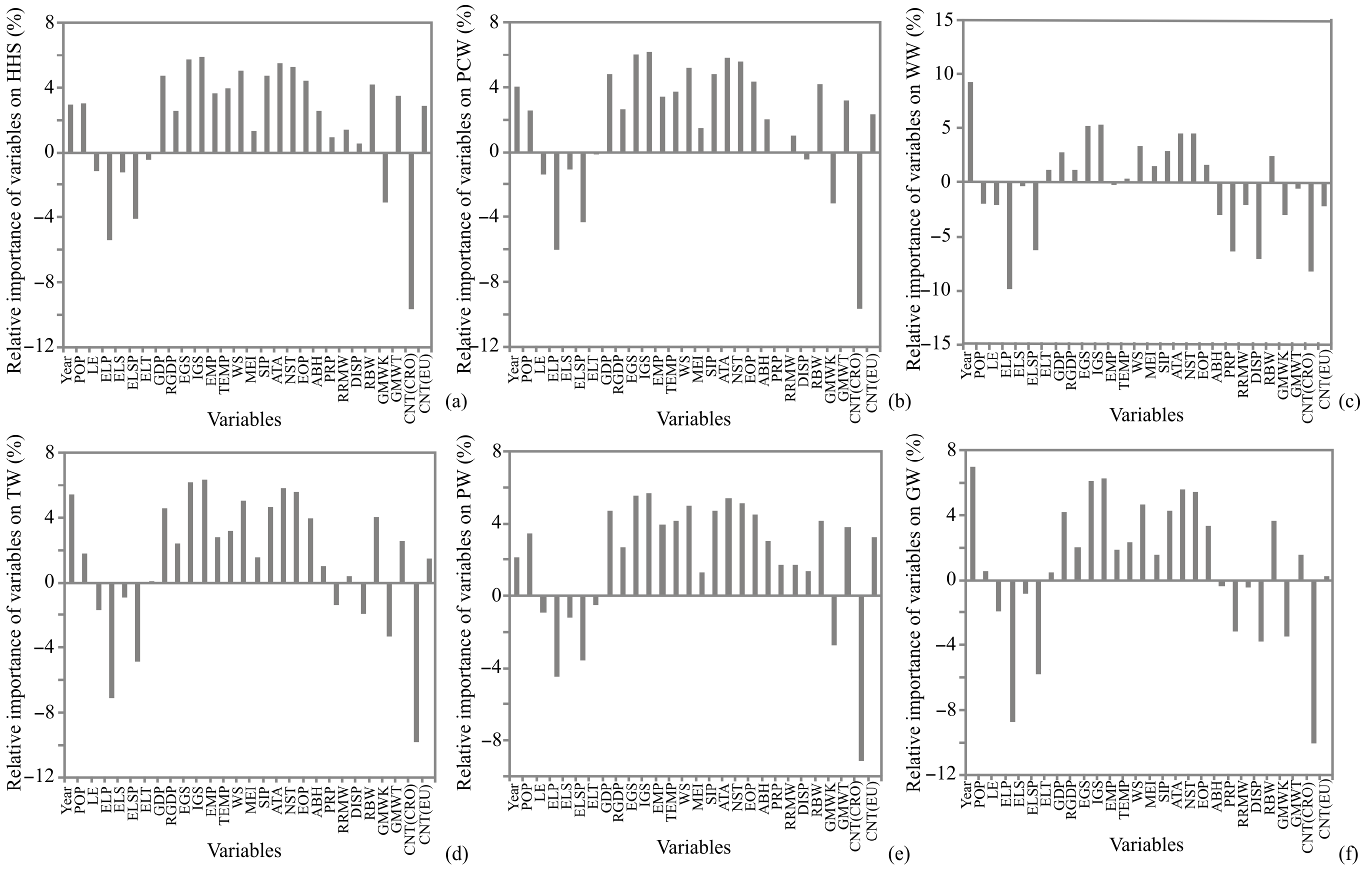

Figure 2. The relative importance of the input variables on: (**a**) HHS, (**b**) PCW, (**c**) WW, (**d**) TW, (**e**) PW and (**f**) GW, determined using the Yoon interpretation method.

In this study, tourism (variables ATA and NST) also showed a positive correlation with the amount of waste generated, Figure 2. Many studies have confirmed that MSW increases with seasonal population in tourist areas or regions. Therefore, it is particularly important in these areas to collect, transport, process and finally dispose of municipal waste in an environmentally friendly, safe and cost-effective manner. In addition to environmental and health problems, improper waste management can also have a negative impact on the attractiveness of a tourist destination [29,30].

It can be concluded that the results of this study are in line with other studies that also confirmed that the number of people (tourists), climatic and economic conditions play an important role in the rate of waste generation [31–33].

It should be noted that with this work, the authors have proven that ANN are capable of obtaining satisfactory forecasting data in a wider area such as the EU area, thus moving away from previous predictions that were mostly of a local or regional nature. In addition, this research confirmed the influence of parameters such as GDP and tourism on waste generation, which can be useful information in the further improvement of the waste management system.

It is also important to emphasize that the amount of MSW waste generated could be influenced by other parameters such as life expectancy, education level, financial development and inequality within the population, changes in employment/unemployment, migration and others. The choice of parameters for building a model depends on the purpose and the research area. Similarly, economic or epidemic crises and deterioration of living standards also affect the amount of municipal waste generated [27,34].

Tables 6 and 7 show the amount of waste that will be generated in the period from 2020 to 2025 by type of waste. Based on the obtained data, it can be concluded that the amount of HHS will decrease, while the amount of recyclable municipal waste (PCW, WW, TW, PW and GW) will increase. The above applies both to data at the EU-27 level and to data in Croatia. This shows similarities in the data, which is also logical, with the assumption that similar data would be obtained by comparing data for other EU member states. The above may also indicate a change in citizens′ awareness and an increasing amount of waste separation. Separate collection of types of waste such as bio-waste and paper is extremely important if the set recycling rates are to be reached.

Table 6. Estimated amounts of generated municipal waste for the EU-27, in thousands of tons.

YEAR	HHS	PCW	WW	TW	PW	GW
2019	118,483.6	39,526.2	42,241.4	1411.6	16,982.8	16,147.1
2020	116,065.8	39,074.9	40,816.1	1267.5	17,464.0	16,381.0
2021	113,648.0	38,623.5	39,390.7	1123.3	17,945.1	16,615.0
2022	111,230.2	38,172.2	37,965.4	979.2	18,426.3	16,849.0
2023	108,812.4	37,720.9	36,540.1	835.0	18,907.4	17,082.9
2024	106,394.6	37,269.5	35,114.7	690.8	19,388.5	17,316.9
2025	103,976.8	36,818.2	33,689.4	546.7	19,869.7	17,550.8

Table 7. Estimated amounts of generated municipal waste for Croatia, in thousands of tons.

YEAR	HHS	PCW	WW	TW	PW	GW
2019	1303.9	202.6	12.1	2.5	51.5	54.9
2020	1287.3	218.7	13.0	2.7	55.9	59.1
2021	1270.7	234.8	14.0	2.9	60.3	63.4
2022	1254.1	250.8	15.0	3.1	64.7	67.6
2023	1237.6	266.9	15.9	3.3	69.1	71.8
2024	1221.0	283.0	16.9	3.5	73.4	76.0
2025	1204.4	299.1	17.9	3.7	77.8	80.2

5. Conclusions

In order to make the waste management system more efficient, it could be helpful to know the quantities generated. The main objective of this research was to construct a model to predict the amount of MSW using an ANN. The input for the development of the model was socio-demographic, economic and industrial data obtained in Croatia, as well as summarized data from the EU. Data from a 25-year period were used to develop the model.

The ANN model was found to be adequate for predicting the output variables (the r^2 values during the training cycle for these variables HHS, PCW, WW, TW, PW and GW were 0.999; 1.0; 1.0; 1.0; 0.999; and 0.999, respectively).

Based on the created model, it is predicted that 103,977,000 tons of HHS, 36,818,000 tons of PCW, 33,689,000 tons of WW, 547,000 tons of TW, 19,870,000 tons of PW and 17,551,000 tons of GW will be produced in the EU-27 area in 2025. At the same time, it is predicted that 1,204,000 tons of HHS, 299,000 tons of PCW, 18,000 tons of WW, 4000 tons of TW, 78,000 tons of PW and 80,000 tons of GW will be generated in Croatia in 2025. The aforementioned predictions could help in the establishment and improvement of the separate waste collection system, which would consequently lead to more efficient recycling and the achievement of the set goals of recycling 55% of municipal waste by 2025.

The results also showed that the most pronounced positive effects on the amount of waste generated were the variables YEAR, GDP, EGS, IGS, WS, SIP, ATA, NST and EOP, which confirmed that gross domestic product, tourism and income have the most pronounced positive impact on the amount of MSW generated.

In order to minimalize negative impact of GDP, earnings and tourism on waste generation and to improve the waste management system, special attention should be directed to eco-tourism, increasing the awareness of citizens with a particular emphasis on preventing the generation of waste in order to reduce the effect of GDP on the generated waste. Recently, more and more attention has been paid to the research of ANN as a tool to predict waste generation, mainly due to the simplicity, accuracy and high error tolerance that allows ANN to work with imperfect or deficient data. It is the quality of the input data that greatly affects the degree of accuracy and future research is needed with a new increased set of input data.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su141610133/s1, Table S1: input variables for the ANN model; Table S2: output variables for the ANN model.

Author Contributions: Conceptualization, E.P. and N.V.; methodology, L.P. and N.V.; software, L.P.; validation, N.V., Ž.Z., J.G. and D.K.G.; formal analysis, L.P. and N.V.; investigation, E.P., L.P. and N.V.; resources, E.P. and N.V.; data curation, L.P.; writing—original draft preparation, E.P., L.P. and N.V.; writing—review and editing, E.P., L.P. and N.V.; visualization, L.P.; supervision, N.V., Ž.Z., J.G. and D.K.G.; project administration, N.V.; funding acquisition, N.V. All authors have read and agreed to the published version of the manuscript.

Funding: This paper has been fully supported by Croatian Science Foundation under the project IP-2018-01-7472 Sludge management via energy crops' production.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

AARD—average absolute relative deviation (%), ABH—available beds in hospitals, ANN—artificial neural networks, ATA—arrivals in collective accommodation establishments, BFGS—Broyden–Fletcher–Goldfarb–Shanno algorithm, CNT—country, DISP—disposal–landfill, EGS—exports of goods and services, ELP—education level: less than primary, primary and lower secondary education, ELS—education level: upper secondary, post-secondary non-tertiary and tertiary education, ELSP—education level: upper secondary and post-secondary non-tertiary education, ELT—education level: tertiary education, EMP—employed persons, EOP—exports of petroleum and petroleum products to partner countries, EU—European Union, GDP—gross domestic product, GMWK—municipal solid waste generation, kilograms per capita, GMWT—municipal solid waste generation, thousand tons, GW—glass waste, HHS—household and similar waste, IGS—imports of goods and services, LE—life expectancy, MBE—mean bias error, MEI—median net equivalized income, MLP—multilayer perceptron network, MPE—mean percentage error, MSW—municipal solid waste, NST—overnight stays in collective accommodation establishments, PCW—paper and cardboard waste, POP—population, PRP—people at risk of poverty or social exclusion, PW—plastic waste, r^2—coefficient of determination, RBW—recycling of bio-waste (composting and anaerobic digestion), RGDP—GDP per capita, RMSE—root mean square error, RRMW—recycling rate of municipal waste (%), SIP—secondary income: personal transfers, current transfers between resident and non-resident households, SOS—sum of squares, SSE—sum of squared errors, TEMP—total employed persons aged 15–64, TW—textile waste, WS—wages and salaries, WW—wood waste, χ^2—reduced chi-squared.

References

1. Blumenthal, K. Generation and Treatment of Municipal Waste. Environment and Energy, 1–12. Source: Eurostat Statistics in Focus 31/2011. 2011. Available online: https://edz.bib.uni-mannheim.de/edz/pdf/statinf/11/KS-SF-11-031-EN.PDF (accessed on 23 March 2021).
2. Vergara, S.E.; Tchobanoglous, G. Municipal Solid Wasteand the Environment: A Global Perspective. *Annu. Rev. Environ. Resour.* **2012**, *37*, 277–309. [CrossRef]
3. Castillo-Giménez, J.; Montañésc, A.; Picazo-Tadeo, A.J. Performance in the treatment of municipal waste: Are European Union member states so different? *Sci. Total Environ.* **2019**, *687*, 1305–1314. [CrossRef] [PubMed]
4. Directive (EU) 2018/851 of the European Paraliament and of the Council of 30 May 2018. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L0851&from=EN (accessed on 23 March 2021).

5. Eurostat. Municipal Waste Statistics. 2021. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Municipal_waste_statistics#Municipal_waste_generation (accessed on 30 March 2022).
6. Eurostat. Municipal Waste by Waste Management Operations. 2022. Available online: https://ec.europa.eu/eurostat/databrowser/view/env_wasmun/default/table?lang=en (accessed on 7 March 2022).
7. Bandara, N.J.G.J.; Hettiaratchi, J.P.A.; Wirasinghe, S.C.; Pilapiiya, S. Relation of waste generation and composition to socio-economic factors: A case study. *Environ. Monit. Assess.* **2007**, *135*, 31–39. [CrossRef] [PubMed]
8. Le Page, M. "Make or break" is hardly hyperbole for the climate negotiations due to reach their climax in November in Glasgow, UK. At the COP26 meeting, nations will have a last chance to really rev up the stuttering motor of climate action and come good on commitments made in Paris in 2015 to limit global warming to a "safe" level of 1.5 °C. *New Sci.* **2021**, *250*, 42–45.
9. Nakicenovic, N.; Lund, P.D. Could Europe become the first climate-neutral continent? *Nature* **2021**, *596*, 486. [CrossRef]
10. Directive 2008/98/EC of the European Parlament and of the Council of 19 November 2008 on Waste and Repealing Certain Directives. Available online: https://eur-lex.europa.eu/eli/dir/2008/98/oj (accessed on 23 March 2021).
11. Ministry of Economy and Sustainable Development. *Municipal Waste Report for 2020*; Ministry of Economy and Sustainable Development: Zagreb, Croatia, 2021.
12. Gertsakis, J.; Lewis, H. *Sustainability and the Waste Management Hierarchy*; EcoRecycle: Victoria, BC, Canada, 2003.
13. Hultman, J.; Corvellec, H. The European Waste Hierarchy: From the sociomateriality of waste to a politics of consumption. *Environ. Plann.* **2012**, *44*, 2413–2427. [CrossRef]
14. Alidoust, P.; Keramati, M.; Hamidian, P.; Amlashi, A.T.; Gharehveran, M.M.; Behnood, A. Prediction of the shear modulus of municipal solid waste (MSW): An application of machine learning techniques. *J. Clean. Prod.* **2021**, *303*, 127053. [CrossRef]
15. Kulisz, M.; Kujawska, J. Predicting of Municipal Waste Generation in Poland Using Neural Network Modeling. *Sustanability* **2020**, *12*, 10088. [CrossRef]
16. Ribić, B.; Pezo, L.; Sinčić, D.; Lončar, B.; Voća, N. Predictive model for municipal waste generation using artificial neural networks—Case study City of Zagreb, Croatia. *Int. J. Energy Res.* **2019**, *43*, 5701–5713. [CrossRef]
17. Abdoli, M.A.; Nezhad, M.F.; Sede, R.S.; Behboudian, S. Longterm Forecasting of Solid Waste Generation by the Artificial Neural Networks. *Environ. Prog. Sustain.* **2011**, *31*, 628–636. [CrossRef]
18. Zade, M.J.G.; Noori, R. Prediction of Municipal Solid Waste Generation by Use of Artificial Neural Network: A Case Study of Mashhad. *Int. J. Environ. Res.* **2008**, *2*, 13–22.
19. Turanyi, T.; Tomlin, A.S. *Analysis of Kinetics Reaction Mechanisms*; Springer: Berlin/Heidelberg, Germany, 2014.
20. Erbay, Z.; Icier, F. Optimization of hot air drying of olive leaves using response surface methodology. *J. Food Eng.* **2009**, *91*, 533–541. [CrossRef]
21. Pezo, M.L.; Stevanović, V.D. Numerical prediction of nucleate pool boiling heat transfer coefficient under high heat fluxes. *Therm. Sci.* **2016**, *20*, S113–S123. [CrossRef]
22. Kojić, P.S.; Popović, S.S.; Tokić, M.S.; Šijački, I.M.; Lukić, N.L.; Jovičević, D.Z.; Petrović, D.L. Hydrodynamics of an external-loop airlift reactor with inserted membrane. *Braz. J. Chem. Eng.* **2017**, *34*, 493–505. [CrossRef]
23. Vladimir, M.; Adamovic, D.Z.; Antanasijevic, M.D.; Ristic, A.A.; Peric, G.; Viktor, V.P. Prediction of municipal solid waste generation using artifcial neural network approach enhanced by structural break analysis. *Environ. Sci. Pollut. Res.* **2016**, *24*, 299–311.
24. Abul, S. Environmental and health impact of solid waste disposal at Mangwaneni dumpsite in Manzini: Swaziland. *J. Sustain. Dev. Afr.* **2010**, *12*, 64–78.
25. Mazza, A.; Piscitelli, P.; Neglia, C.; Rosa, G.; Lannuzzi, L. Illegal dumping of toxic waste and its efect on human health in Campania, Italy. *Int. J. Environ. Res. Public Health* **2015**, *12*, 6818–6831. [CrossRef]
26. Mohsin, M.; Chinyama, A. Impacts of solid waste management practices on environment and public health: A case of Bahawalpur City, Pakistan. *J. Environ. Agric. Sci.* **2016**, *9*, 69–79.
27. Namlis, K.-G.; Komilis, D. Influence of four socioeconomic indices and the impact of economic. *Waste Manag.* **2019**, *89*, 190–200. [CrossRef]
28. Kumar, J.S.; Venkata Subbaiah, K.V.; Prasada Rao, P.V. Prediction of Municipal Solid Waste with RBF NetWork—A Case Study of Eluru, A.P., India. *Int. J. Innovation. Manag. Technol.* **2011**, *2*, 238–243.
29. Arbulú, I.; Lozano, J.; Rey-Maquieira, J. Tourism and solid waste generation in Europe: A panel data assessment of the Environmental Kuznets Curve. *Waste Manag.* **2015**, *46*, 628–636. [CrossRef] [PubMed]
30. Mateu-Sbert, J.; Ricci-Cabello, I.; Villalonga-Olives, E.; Cabeza-Irigoyen, E. The impact of tourism on municipal solid waste generation: The case of Menorca Island (Spain). *Waste Manag.* **2013**, *33*, 2589–2593. [CrossRef] [PubMed]
31. Jahandideh, S.; Jahandideh, S.; Barzegari Asadabadi, E.; Askarian, M.; Movahedi, M.M.; Hosseini, S.; Jahandideh, M. The use of artificial neural networks and multiple linear regression to predict rate of medical waste generation. *Waste Manag.* **2009**, *29*, 2874–2879. [CrossRef] [PubMed]
32. Trang, P.T.T.; Dong, H.Q.; Toan, D.Q.; Hanh, N.T.X.; Thu, N.T. The effects of socio-economic factors on household solid waste generation and composition A case study in Thu Dau Mot. *Vietnam. Energy Procedia* **2017**, *107*, 253–258. [CrossRef]
33. Wu, F.; Niu, D.; Dai, S.; Wu, B. New insights into regional differences of the predictions of municipal solid waste generation rates using artificial neural networks. *Waste Manag.* **2020**, *107*, 182–190. [CrossRef]

34. Ali, S.A. E-waste generation and its possible impacts on environment and human health: A study on Kolkata. *Asian Profile* **2017**, *45*, 77–94.
35. Madaleno, M. Environmental pollution, waste generation and human health. *Biomed. J. Sci. Tech. Res.* **2018**, *10*, 10. [CrossRef]
36. Buenrostro, O.; Bocco, G.; Vence, J. Forecasting generation of urban solid waste in developing countries—A case study in Mexico. *J. Air Waste Manag. Assoc.* **2001**, *51*, 6–93. [CrossRef]
37. Abbasi, M.; El Hanandeh, A. Forecasting municipal solid waste generation using artificial intelligence modelling approaches. *Waste Manag.* **2016**, *56*, 13–22. [CrossRef]
38. Johnson, D.P.; Stanforth, A.; Lulla, V.; Luber, G. Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. *Appl. Geogr.* **2012**, *35*, 23–31. [CrossRef]
39. Yun, T.S.; Jeong, Y.J.; Han, T.S.; Youm, K.S. Evaluation of thermal conductivity for thermally insulated concretes. *Energ. Build.* **2013**, *61*, 125–132. [CrossRef]
40. Kleijnen, J.P.C. Design and Analysis of Simulation Experiments. In *Statistics and Simulation*; Pilz, J., Rasch, D., Melas, V., Moder, K., Eds.; IWS 2015, Springer Proceedings in Mathematics & Statistics 2018; Springer: Cham, Switzerland, 2015; Volume 231.
41. Pavlić, B.; Pezo, L.; Marić, B.; Peić Tukuljac, L.; Zeković, Z.; Bodroža Solarov, M.; Teslić, N. Supercritical fluid extraction of raspberry seed oil: Experiments and modeling. *J. Supercrit. Fluid.* **2020**, *157*, 104687. [CrossRef]
42. Kollo, T.; von Rosen, D. *Advanced Multivariate Statistics with Matrices*; Springer: Dordrecht, The Netherlands, 2005.
43. Pezo, L.; Ćurčić, B.L.; Filipović, V.S.; Nićetin, M.R.; Koprivica, G.B.; Mišljenović, N.M.; Lević, L.B. Artificial neural network model of pork meat cubes osmotic dehydratation. *Hem. Ind.* **2013**, *67*, 465–475. [CrossRef]
44. Emadaldin Mohammadi, G.; Behnood, A. Application of soft computing methods for predicting the elastic modulus of recycled aggregate concrete. *J. Clean. Prod.* **2018**, *176*, 1163–1176.
45. Ochoa-Martínez, C.I.; Ayala-Aponte, A.A. Prediction of mass transfer kinetics during osmotic dehydration of apples using neural networks. *LWT-Food Sci.Technol.* **2007**, *40*, 638–645. [CrossRef]
46. Berrueta, L.A.; Alonso-Salces, R.M.; Héberger, K. Supervised pattern recognition in food analysis. *J. Chromatogr. A.* **2007**, *1158*, 196–214. [CrossRef]
47. Doumpos, M.; Zopounidis, C. Preference disaggregation and statistical learning for multicriteria decision support: A review. *Eur. J. Oper. Res.* **2011**, *209*, 203–214. [CrossRef]
48. Taylor, B.J. *Methods and Procedures for the Verification and Validation of Artificial Neural Networks*; Springer Science & Business Media: New York, NY, USA, 2006.
49. Yoon, Y.; Swales, G.; Margavio, T.M. A Comparison of Discriminant Analysis versus Artificial Neural Networks. *J. Oper. Res. Soc.* **2017**, *44*, 51–60. [CrossRef]
50. Rajković, D.; Marjanović Jeromela, A.; Pezo, L.; Lončar, B.; Zanetti, F.; Monti, A.; Kondić Špika, A. Yield and Quality Prediction of Winter Rapeseed—Artificial Neural Network and Random Forest Models. *Agronomy* **2022**, *12*, 58. [CrossRef]
51. Montgomery, D.C. *Design and Analysis of Experiments*, 2nd ed.; John Wiley and Sons: New York, NY, USA, 1984.
52. Chattopadhyay, P.B.; Rangarajan, R. Application of ANN in sketching spatial nonlinearity of unconfined aquifer in agricultural basin. *Agric. Water Manag.* **2014**, *133*, 81–91. [CrossRef]