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Artificial Intelligence (AI) applied to waste management: A contingency measure to fill out the lack of information resulting from restrictions on field sampling

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ABSTRACT

Waste characterization is essential in planning to reduce waste, create recycling programs and properly use public funds. Traditionally, waste characterization is successfully performed by on-site sampling. This monitoring requires specialized professionals following safety protocols to decrease the health risks associated with the waste handling. However, on-site sampling is susceptible to restrictions in mandatory quarantine situations. Here we show the possibility of using Artificial Intelligence applied to waste management. We identified an Artificial Neural Network (ANN) model fed by combination of population, Gross Domestic Product, Potable Water Supply and Sanitation System data that could be used to fill gaps related to the pandemic period. The modified model predictions were successful due to the adaptive capacity of the ANN-based models. Our results demonstrate that ANN can be used in contingency plans to predict the gravimetric composition and specific weight of Municipal Solid Waste, based on strategically chosen socioeconomic information. We anticipate that our model will be a starting point for more sophisticated computational models. It will allow not only the filling of gaps but also the use for auditing, because it allows analyzing the consistency of gravimetric composition and specific weight data provided by third parties.

Introduction

The COVID-19 pandemic changed the world, bringing numerous consequences for the economy, employment and everyday life (Ikiz et al., 2021). The large number of infection cases and the discovery of different variants have elevated concerns around the world about the risks of contamination associated with solid waste management, mostly because of the sudden increase in infectious waste (Penteado and Castro, 2021).

It is mandatory to respect the limitations imposed by virulent agents such as coronavirus Sars-CoV-2 (ABES, 2020; ABRELPE, 2020). However, smart cities must maintain a consistent level of quality in waste management to avoid other risks. Therefore, contingency plans related to waste collection and treatment must include healthy and safe ways to monitor the waste produced, seeking to protect lives and livelihoods both of formal and informal workers who are involved in waste management system (INEP, 2020).

The unexpected fluctuations in waste composition and quantity require a dynamic response from policymakers (Sharma et al., 2020), increasing demand for new products and services that can balance resources and waste management with health and safety concerns (Neumeyer et al., 2020).

The Municipal Solid Waste (MSW) can be analyzed by its physical, chemical and biological properties. The physical characteristics, such as gravimetric composition and specific weight, are very relevant to planning suitable services of urban cleaning (MAHLER, 2010 as cited in Schuler, 2010) recycling programs, and other specific resource management practices. Thus, reliable models for estimating waste generation are crucial to allow better use of public funds Araújo (2012).

The use of Artificial Neural Networks (ANN) for gravimetric composition and specific weight estimation from socioeconomic data is not a widespread practice. The Brazilian waste management sector adopts the sampling procedures, which demands employment of specialized staff and consumes significant amount of time and financial resources. Furthermore, such traditional methods can be dangerous to the health of employees responsible for handling waste, especially in pandemic situations such as COVID-19.

Considering that the residues reflect the daily behaviors of society it is possible infer that there is a predictability relationship between characteristics of society and properties of the waste produced by it.

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In this sense, this paper proposes an estimation method of gravimetric composition and specific weight of MSW, based in ANN, which could be used for frequently situations faced by public managers and other government officials, including pandemic situations.

The core of this paper emerged from the analysis of data about waste management carried out by the city hall of one of the most important municipalities in Brazil. An official document (IPP, 2022c) reveals that the COVID-19 pandemic prevented obtaining essential information for waste management stating that "(…) *Due to the pandemic, the complete characterization of waste was not carried out for the year 2020, therefore the information was not broken down by Planning Area* (…)" (translated from Portuguese to English).

In this paper, the standard method developed by Thomaz (2016) was modified to suit the available input data, demonstrating the versatility of ANN.

Materials and methods

Theoretical basis

THOMAZ (2016) tested different scenarios to understand how the socioeconomic characteristics of the population of a given region determines properties of MSW, allowing a reliable prediction of solid waste produced, knowing only its population profile. It is a clean technique without the need for waste handling by workers.

The ANN used in this method are computational model capable of simulating the behavior of the animal brain, which is an organ able to learn without know the algorithm that produces the problem, able to generalize and robust. The use of ANN allows the understanding of complex phenomena as well as allows the estimation of dependent variables, making use of other more accessible variables (Calôba, 2002).

It is important to note that the data collection stage is one of the most time-consuming steps in carrying out this work because a huge amount of raw data should be obtained from different sources, in different formats and with different reference parameters. Fortunately, nowadays, cognitive computing can be used to improve big data analytics (Gupta et al., 2018) which greatly expands the range of application of ANN solution presented in this paper.

Study area

The study area chosen to validate the model was the Municipality of Rio de Janeiro, capital of the State of Rio de Janeiro, located at southeast region of Brazil. Besides being one of the main economic and financial regions of the country, Rio de Janeiro is known internationally for its attractive culture and famous landmarks, including the giant statue of Christ the redeemer at the top of Corcovado Mountain, named one of the New Seven Wonders of the World; Sugarloaf Mountain with its cable car; and Maracanã Stadium, one of the world's largest soccer stadiums.

The main forms of final destination of MSW in the study area are recycling, composting and disposal in landfills. The continuous waste characterization allows the best knowledge of waste produced what is essential to respect the technical, economic and environmental parameters required for environmentally appropriate disposal.

In the year of 2010, the population resident in the Municipality was 6,320,446, equivalent to almost 40% of the population of the State of Rio de Janeiro (IBGE, 2010). Ten years later, in the year 2020, the population in the municipality of Rio de Janeiro grew to 6,747,815.00 inhabitants (IPP, 2022d).

The collection of MSW in the Municipality of Rio de Janeiro is carried out by the Municipal Cleaning Company (COMLURB) which provides numerous data about regarding the collection and disposal of MSW, including data on gravimetric composition and specific gravity from the year 1995 to 2021 (IPP, 2022c).

The socioeconomic data of the population studied were compiled from various sources such as Demographic Census, National Household Sample Survey, which are the responsibility of the Brazilian Institute of Geography and Statistics (IBGE). In order to avoid dependence on a single source of data, relevant data were also obtained from the Municipal Institute of Urbanism Pereira Passos (IPP), among other sources.

Computational tool

MATLAB software was selected to program the ANN because it presented the best performance among the other tested programs such as "Weka", a freeware from the University of Waikato, and the paid Excel add-in called "NeuralTools" from Palisade company.

Socioeconomic and MSW data were grouped into spreadsheets that were filtered, processed and transformed into a detailed information database, used to assemble sets "inputs-targets" compatible with the MATLAB workspace arrangement (Fig. 1).

It was chosen networks fed by multiple layers of output nodes, or Multilayer Perceptrons (MLP) (Fig. 2). They have one or more hidden (intermediate) layers where each neuron has direct connections to neurons in the adjacent layer. In this case, there is also a comparison between the results and the error found is inserted back into the network to adjust the values, further decreasing the value of the error function.

The number of hidden layers adopted was chosen according to the empirical method proposed by Beale (2015) avoiding excessive layers which could cause overfitting problem and harm the process of generalization.

Tests with ten hidden layers were started and the number of layers was increased to hundreds of them. The simulations carried out with more than five hundred layers required a large computational effort and the results were not satisfactory. For this study it was observed that a few dozen layers are enough.

In the regression graphic representation (Fig. 3) it is observed that for the forecasts made with 30 hidden layers, the data present a very good fit, with an "R" value greater than 0.99.

At the end of the process an instruction automatically creates the array "ResultadoPHL", containing the simulation results within the MATLAB Workspace. To check robustness of the forecasts, the outputs are inspected through Eqs. (1) and (2):

$$\text{Absolut Error} = \text{Reference Value} - \text{Estimated Value} \tag{1}$$

$$\text{Relative Error} = \frac{\text{Reference Value} - \text{Estimated Value}}{\text{Reference Value}} \tag{2}$$

Results e discussion

Standard theoretical model

For the Municipality of Rio de Janeiro, the combination of population data, Gross Domestic Product (GDP), total annual electricity consumption and retail sales index make up the standard theoretical model proposed by THOMAZ (2016) for the period 2004–2011, therefore they were used to build the standard MATLAB input database (Table 1) and choose targets (Table 2). The results and the compliance check can be seen in Table 3.

The relative errors of the predictions (Table 3) were less than 10%, except for the fraction "metal" (relative error 11.6%) and for the fraction "other residues" (relative error 25.3%). This will be the tolerable error threshold for predictions made by variations of this standard method. The MATLAB code of this standard model is available at the **Appendix A**.

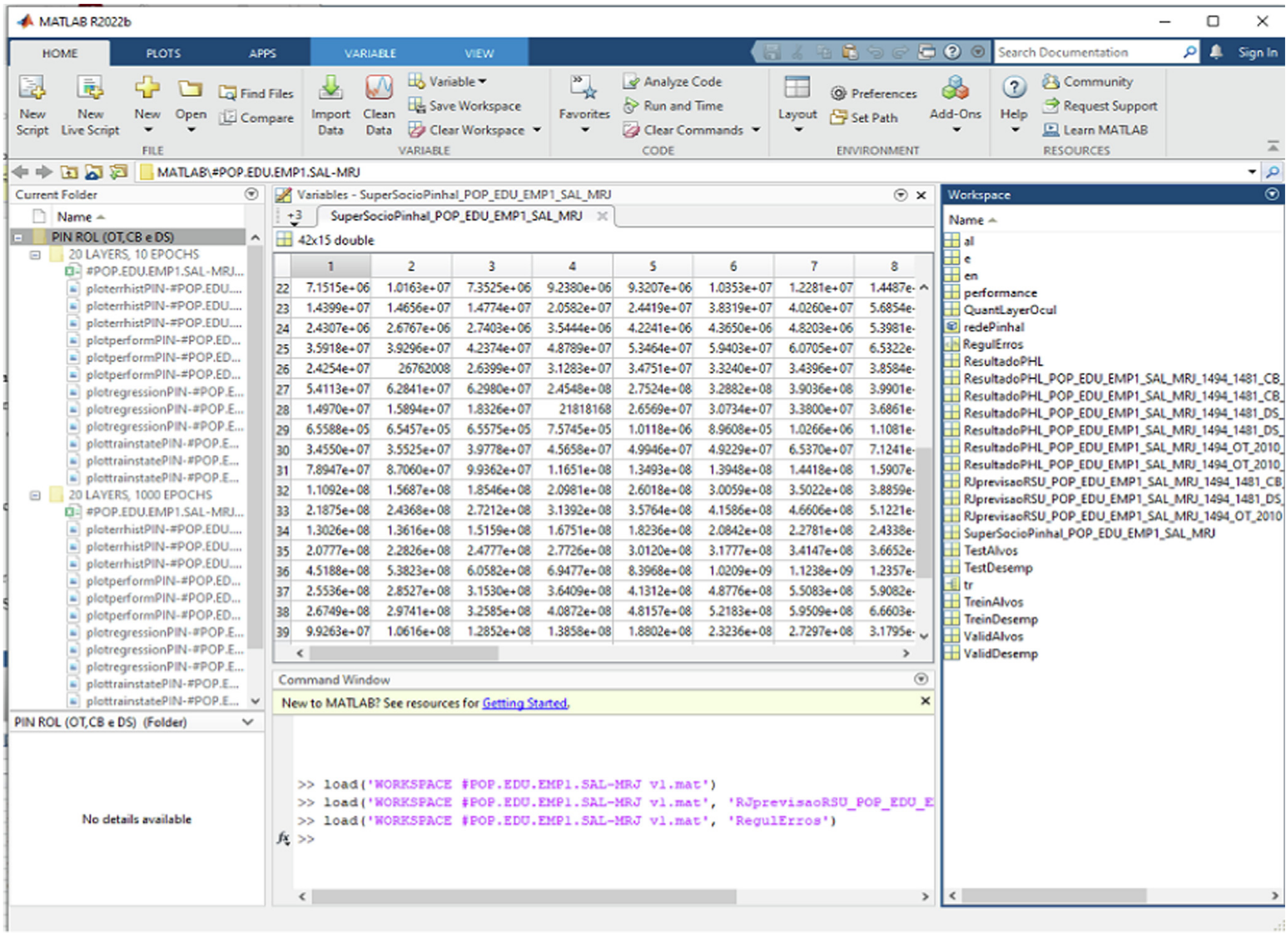

Fig. 1. MATLAB workspace arrangement.

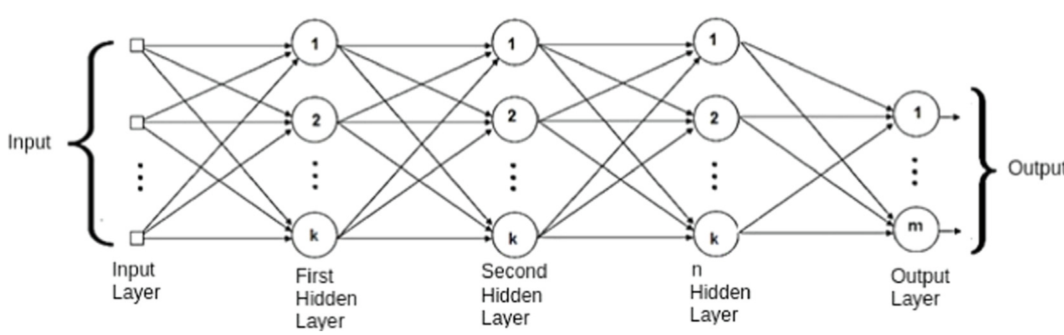

Fig. 2. Schematic diagram of a Multilayer Perceptrons (MLP) neural network. Source: Author, based on Haykin (2001).

Evaluating the modified model

The use of input variables that are not relevant for determining the outputs causes the introduction of noise at the input and impairs the performance of the network while the elimination of input variables that contain relevant information about the outputs results in the deterioration in the accuracy of the output results prediction (Calôba, 1992, 2005).

Considering that this paper proposes a contingency measure to fill in the lack of information resulting from restrictions on field sampling due to mandatory quarantines to combat pandemics, it is necessary to be able to make predictions for the year 2020.

However, the impacts caused by the pandemic on commerce in the Municipality of Rio de Janeiro were so intense that there is no data available of retail sales index for the period of the pandemic. Then, total annual electricity consumption and retail sales index data were replaced by Potable Water Supply (IPP, 2022a) and Sanitation System (IPP, 2022b) data in the modified model.

To allow for comparability, including adopting the same original targets (Table 2), data from the same period (2004–2011) were used to build the modified MATLAB input database (Table 4). The results and verification of compliance can be seen in Table 5.

The relative forecast errors (Table 5) were less than 10% for all fractions, therefore, the result of the modified method was better than

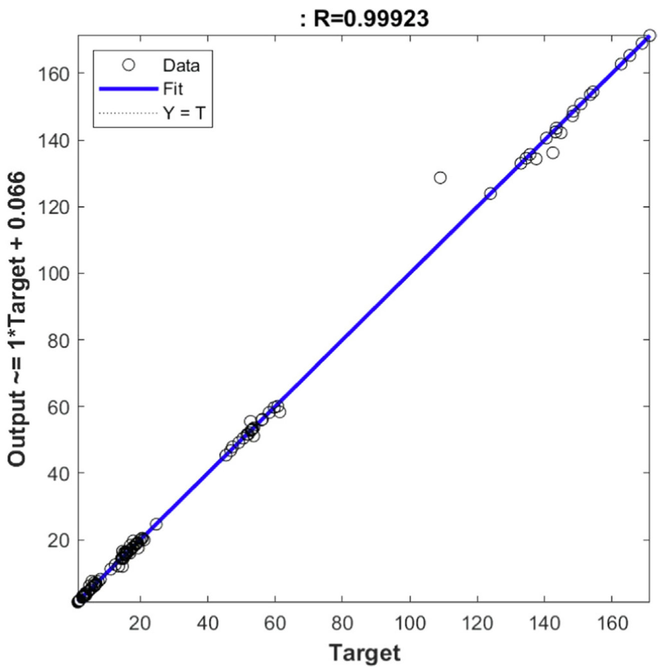

Fig. 3. Regression graphic representation.

that obtained by the original method, consequently, the method was validated. The MATLAB code of this modified model is available at the **Appendix B**.

Table 3
Compliance check for the year 2011 gravimetric composition and specific weight -prediction results of standard model.

COMPLIANCE CHECK		Reference 2011	Estimated 2011	Error	
				Absolut	Relative
Gravimetric composition	Paper - Cardboard	16.84%	16.82%	0.0163	0.10%
	Plastic	19.29%	18.94%	0.3509	1.82%
	Glass	3.19%	2.89%	0.3013	9.46%
	Metal	1.68%	1.49%	0.1946	11.57%
	Others	6.33%	4.73%	1.6016	25.29%
	Organic matter	52.68%	55.14%	−2.4646	−4.68%
Specific Weight (Kg/m^3)		109.09	105.55	3.5361	3.24%

Forecast for the pandemic period based on the modified model

For the pandemic period it is proposed the combination of population, Gross Domestic Product (GDP), Potable Water Supply and Sanitation System data to build the standard MATLAB input database (Table 6) and choose targets (Table 7). The results and the compliance check can be seen in Table 8.

Relative forecast errors (Table 8) were less than 10% for all fractions, therefore, the result of the modified method indicates that its use for forecasts corresponding to the pandemic period may be appropriate.

It is important to emphasize that the reference values for the year 2020 were made available by the Municipality of Rio de Janeiro with significant delay, postponing the conclusion of this paper, since it

Table 1
Standard input database to feed the algorithm developed in MATLAB.

INPUTS		2004	2005	2006	2007	2008	2009	2010	2011
Population		6,051,399	6,094,183	6,136,652	6,093,472	6,161,047	6,186,710	6,320,446	6,355,949
GDP Present Value (millions R$)		112,675	117,772	128,026	140,095	158,757	170,517	190,018	209,366
Classes of electricity consumption (MWh)	Residential	4,840,630	5,264,761	5,286,605	5,394,924	5,382,944	5,759,607	5,985,329	6,018,867
	Industrial	2,495,426	2,251,276	1,852,207	3,875,665	3,891,549	2,583,374	2,860,884	2,562,750
	Commercial	4,343,455	4,685,725	5,066,104	4,963,312	5,055,236	5,280,937	5,535,628	5,684,810
	Rural	1,779	1,894	1,888	2,109	2,130	2,197	2,245	2,360
	Public powers	936,013	1,021,809	1,224,161	1,154,018	1,149,348	1,229,854	1,245,820	1,286,482
	Street lighting	423,173	504,554	166,819	461,413	447,082	435,053	442,492	448,021
	Public service	588,144	570,904	1,104,240	603,604	609,149	783,308	796,484	824,004
	Own consumption	42,669	40,997	66,768	65,446	59,100	55,815	66,511	74,411
Sectors of Commerce	Hypermarkets, supermarkets, food products, beverages and tobacco	106.4	107.9	115.4	114.9	121.4	128.9	140.0	143.1
	Fabrics, clothing and footwear	101.8	107.7	102.1	118.2	121.1	106.2	117.4	123.8
	Furniture and household appliances	123.8	136.9	141.3	164.5	182.5	193.6	240.3	285.9
	Pharmaceutical, medical, orthopedic, perfumery and cosmetics articles	103.4	104.7	102.4	105.8	118.2	129.1	136.8	143.5
	Equip. and office supplies, computer and communication	90.8	169.0	259.9	399.0	642.4	749.5	671.6	689.4
	Books, newspapers, magazines and stationery	85.2	82.0	95.9	97.7	101.1	105.2	106.8	107.6
	Other articles of personal and domestic use	121.0	134.4	165.4	191.9	220.3	243.8	245.8	263.7

Table 2
Targets selected for the year 2011 gravimetric composition and specific weight prediction.

TARGETS		2004	2005	2006	2007	2008	2009	2010	2011
Gravimetric composition	Paper - Cardboard (%)	12.48	13.51	14.83	14.56	15.96	16.08	16.46	Target
	Plastic (%)	15.44	15.34	14.69	17.15	18.58	20.31	19.11	Target
	Glass (%)	3.23	3.24	2.71	2.96	2.79	2.84	2.96	Target
	Metal (%)	1.70	1.65	1.61	1.59	1.51	1.74	1.40	Target
	Others (%)	7.42	5.52	4.82	5.51	4.95	5.40	5.04	Target
	Organic matter (%)	59.73	60.74	61.35	58.23	56.21	53.63	55.02	Target
Specific Weight (Kg/m^3)		153.60	148.35	144.93	143.57	140.60	123.96	111.15	Target

Table 4
Modified input database to feed the algorithm developed in MATLAB.

INPUTS		2004	2005	2006	2007	2008	2009	2010	2011
Population		6,051,399	6,094,183	6,136,652	6,093,472	6,161,047	6,186,710	6,320,446	6,355,949
GDP Present Value (millions R$)		112,675	117,772	128,026	140,095	158,757	170,517	190,018	209,366
Potable Water Supply	Number of active water connections	739,153.00	705,410.00	691,886.00	747,043.00	789,295.00	882,124.00	907,052.00	805,149.00
	Number of autonomous units supplied	1,795,762.00	1,817,843.00	1,709,990.00	1,809,128.00	1,967,361.00	2,121,065.00	2,175,776.00	1,920,685.00
	Extension of the supply network (km)	9,548.00	9,548.00	9,609.00	9,673.00	9,758.00	9,852.00	9,946.62	9,810.00
	Produced and/or Imported (m^3)	1,058,302.33	1,083,899.84	1,081,641.60	1,081,641.60	1,085,300.00	1,018,679.23	1,027,087.00	1,077,292.00
	Measurement by hydrometers (m^3)	342,909.74	341,135.73	351,292.07	349,881.72	351,547.00	376,442.00	386,152.00	361,928.00
	Effective consumption (m^3)	493,855.00	472,763.00	441,299.21	499,780.52	677,593.00	611,203.99	626,969.00	441,962.00
Sanitation System	Percentage of population served (%)	81.51	82.91	82.01	69.99	82.39	70.12	77.85	68.65
	Number of active connections	636,179.00	644,809.00	647,956.00	511,525.00	675,184.00	692,079.00	709,401.00	489,635.00
	Number of active autonomous units	1,635,206.00	1,641,716.00	1,633,070.00	1,427,879.00	1,708,301.00	1,577,632.00	1,617,118.00	1,452,673.00
	Volume collected (1,000 m3/year)	371,020.00	348,923.00	372,325.00	357,282.00	378,348.00	376,099.31	385,513.00	340,875.00
	Treated volume (1,000 m3/year)	306,700.00	291,896.00	300,628.80	299,532.07	322,557.00	325,401.00	325,542.00	333,421.00
	Extension of the sewage network (Km)	4,192.00	4,227.00	4,256.00	4,292.00	4,308.00	4,464.00	4,474.00	4,325.00

Table 5
Compliance check for the year 2011 gravimetric composition and specific weight -prediction results of modified model.

COMPLIANCE CHECK		Reference 2011	Estimated 2011	Error	
				Absolut	Relative
Gravimetric composition	Paper - Cardboard	16.84%	16.56%	0.2720	1.62%
	Plastic	19.29%	18.84%	0.4482	2.32%
	Glass	3.19%	3.11%	0.0804	2.52%
	Metal	1.68%	1.62%	0.0573	3.41%
	Others	6.33%	6.74%	−0.4039	−6.38%
	Organic matter	52.68%	53.13%	−0.4539	−0.86%
Specific Weight (Kg/m^3)		109.09	111.09	−2.0000	−1.83%

Table 6
Pandemic period input database to feed the algorithm developed in MATLAB.

INPUTS		2012	2013	2014	2015	2016	2017	2018	2019	2020
Population		6,390,290.00	6,429,923.00	6,453,682.00	6,476,631.00	6,498,837.00	6,520,266.00	6,688,927.00	6,718,903.00	6,747,815.00
GDP Present Value (millions R$)		253,200.79	284,299.25	300,270.15	320,186.62	328,440.48	337,675.26	363,403.23	354,932.61	331,279.90
Potable Water Supply	Number of active water connections	918,132.00	992,693.00	972,569.00	1,067,360.00	1,073,813.00	1,077,384.00	1,086,868.00	1,357,211.00	1,407,758.00
	Number of autonomous units supplied	2,199,829.00	2,219,225.00	2,234,347.00	2,396,224.00	2,423,676.00	2,433,242.00	2,450,920.00	2,613,356.00	2,715,431.00
	Extension of the supply network (km)	10,112.00	10,210.69	10,290.60	10,352.52	10,891.20	10,710.21	10,736.86	10,839.45	10,850.70
	Produced and/or Imported (m^3)	1,034,288.00	1,036,367.00	1,044,988.00	1,087,094.00	1,087,546.00	1,086,049.00	1,102,521.00	1,111,972.00	1,106,319.00
	Measurement by hydrometers (m^3)	390,421.00	393,863.00	396,546.84	425,276.00	429,917.00	431,846.00	434,983.00	358,579.00	260,387.90
	Effective consumption (m^3)	660,085.00	704,077.00	708,874.68	760,232.00	768,528.00	771,976.00	777,585.00	527,345.13	405,461.48
Sanitation System	Percentage of population served (%)	78.25	80.95	83.11	83.08	85.16	85.98	85.10	86.27	87.95
	Number of active connections	723,946.00	739,072.00	786,727.00	796,590.00	819,368.00	832,277.00	847,533.00	965,444.00	879,016.00
	Number of active autonomous units	1,650,877.00	1,684,416.00	1,764,448.00	1,781,002.00	1,817,185.00	1,839,249.00	1,869,049.00	2,124,514.00	2,177,739.00
	Volume collected (1,000 m3/year)	414,798.20	461,896.83	469,285.69	455,815.22	449,063.98	449,781.11	455,922.73	427,367.57	393,233.53
	Treated volume (1,000 m3/year)	330,157.72	332,189.48	334,572.81	338,008.67	342,099.71	355,103.17	333,335.09	346,019.45	341,556.81
	Extension of the sewage network (Km)	5,394.00	5,396.00	5,982.00	6,254.23	6,665.05	6,428.24	6,555.57	6,765.73	6,925.65

Table 7
Targets selected for the year 2020 gravimetric composition and specific weight prediction.

Targets		2012	2013	2014	2015	2016	2017	2018	2019	2020
Gravimetric composition	Paper - Cardboard (%)	15.99	16.83	15.62	15.14	14.82	14.70	14.31	14.63	Target ⋔
	Plastic (%)	19.14	18.99	21.01	17.84	20.24	24.66	15.33	15.72	Target ⋔
	Glass (%)	3.28	3.39	3.46	3.69	3.55	3.46	3.48	3.58	Target ⋔
	Metal (%)	1.57	1.63	1.65	1.68	1.65	1.51	1.81	1.75	Target ⋔
	Others (%)	6.75	6.35	6.26	8.05	6.51	6.46	14.56	16.99	Target ⋔
	Organic matter (%)	53.28	52.81	52.00	53.60	53.23	49.21	50.51	47.33	Target ⋔
Specific Weight (Kg/m^3)		133.02	134.55	142.51	143.33	162.80	171.36	148.58	137.56	Target ⋔

Table 8
Compliance check for the year 2020 gravimetric composition and specific weight -prediction results for the pandemic period.

Compliance check		Reference 2020	Estimated 2020	Error	
				Absolut	Relative
Gravimetric composition	Paper - Cardboard	11.17%	11.58%	−0.4118	−3.69%
	Plastic	15.69%	15.88%	−0.1875	−1.19%
	Glass	4.37%	4.56%	−0.1830	−4.19%
	Metal	1.51%	1.42%	0.0858	5.69%
	Others	20.48%	18.78%	1.6935	8.27%
	Organic matter	46.78%	47.78%	−0.9989	−2.14%
Specific Weight (Kg/m^3)		135.72	133.25	2.4664	1.82%

would be innocuous to publish this study before the validation of the result.

Conclusions

The understanding of the socioeconomic phenomenon that governs the production of residues leads to the conclusion that there is no linear relation between the characteristics of the MSW and the socioeconomic factors of the population that produced it, however, this has not become a problem for the use of ANN, since this computational method is versatile and suitable for non-linear situations and singular complexities, being able to extrapolate data based on the rates of variation of the socioeconomic factors used.

Different socioeconomic indicators can be used in the forecasts, but since the forecasts obtained through the ANN are backed by third party data, the results obtained through them will be as reliable as the predictions of the institutions that serve as data feeders. The use of unreliable data makes the forecasting process merely mathematical and therefore has no practical utility, so, it is recommended that special attention be given to the part of data collection and validation of sources.

The evolution of technology has enabled sophisticated computation tools, once reserved for a few segments, to be used on a large scale for the good of society. The choice of ANN technique to predict the gravimetric composition of MSW is more efficient than on-site sampling since the latter requires the employment of specialized professionals and require a significant amount of time and could be dangerous to the employees responsible for handling waste, especially in pandemic situations such as COVID-19.

Despite errors greater than 5%, acceptable during the development period (Mendel and McLaren, 1970), the use of the technique would be useful to fill in the information resulting from restrictions on field sampling due to mandatory quarantines to combat pandemics.

Furthermore, this tool is highly recommended to support policy-makers in their resource management strategies including integrated recycling programs. In addition, the tool is versatile and can also be used by for auditing, since it allows analyzing the consistency of gravity data and specific weight provided by third parties, making it easier for the auditor to decide where to concentrate efforts in the search for suspicious situations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wmb.2023.06.002.

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