PREDICTION OF CONTAINER FILLING FOR THE SELECTIVE WASTE COLLECTION IN ALGECIRAS (SPAIN)

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ABSTRACT

The aim of this study is to create an intelligent system that improves the efficiency of garbage collection, (cardboard waste, in this particular case). The number of cardboard containers to be collected each day will be determined based on a prediction made on the filled volume recorded in each container. It will be reflected in the cost and fuel savings, reducing emissions and contributing to environmental sustainability. These results will allow planning the sequence of waste removal, which means the optimal collection route considering restrictive parameters such as the type of truck, the location of containers, collection times by zones, and the availability of working staff.

A filling prediction system is proposed based on real historical data provided by the current waste collection company in Algeciras (ARCGISA). To achieve this objective, an intelligent system is designed using predictive analytics and several methods based on machine learning, modelling the collection system as a classification model, comparing the results from a statistical point of view (using sensitivity, specificity, etc.). The results obtained with the best-tested method indicate an improvement average rate of 26% in sensitivity performance index and 67% in specificity performance index.

Currently, waste collection is carried out without predictive analysis. The relevance of an efficient waste collection system is becoming increasingly important. Achieving optimal waste collection will result in improved service to citizens, cost savings for the administration, and significant environmental improvements.

1. INTRODUCTION

This project aims to create a 'smart' system that improves the efficiency of waste collection, in this case, cardboard. This system solves two major problems faced by waste collection companies. On the one hand, to determine which containers should be collected each day according to their filling volume and, on the other hand, to obtain the collection order, i.e. to know which is the optimal route for the collection of the containers. This will save costs and fuel, thereby reducing emissions and contributing to environmental sustainability.

A filling prediction system is proposed based on real data, provided by the company ARCGISA (Agua y Residuos del Campo de Gibraltar, S.A.), from which the optimum collection time will be estimated based on an ideal filling level and the optimum route for collecting the containers will be obtained. A significant reduction in management time, economic savings and an improvement in the quality of the service provided to citizens are expected, increasing urban sustainability. In summary, a dynamic system of container filling predictions is proposed to estimate the optimal filling time and calculate the most favourable route for collection. To achieve these objectives, the project aims to design an intelligent system using predictive analytics and machine learning to improve the planning and efficiency of selective waste collection, based on the use of neural networks.

Each person generates a large amount of waste every day. The life cycle of waste harms the environment. Efficient waste management has become a necessity to preserve available natural resources. For this reason, the objective is to achieve urban sustainability and guarantee the quality of life of citizens. Furthermore, waste treatment offers a business opportunity, since the recycling of products such as cardboard allows them to be reused for the production of new products. The management of this waste for further treatment is a chain that involves the collection, transport, processing, recycling and monitoring of new products.

Increasingly, organisations and companies assume that environmental improvements in their production systems and services are competitive advantages, either by reducing economic costs or by improving the image of the product in the eyes of better informed and aware consumers. To reduce waste generation and improve sustainability, tools and mechanisms such as life cycle analysis (LCA) and eco-design are used.

LCA is a methodology used to assess the potential impact on the environment of a product, process or activity throughout all its stages of existence (extraction of raw materials, production, distribution, use, end of life). At each stage, the energy and resource inputs and potential outputs in the form of emissions, discharges and wastes associated with the system under assessment are quantified.

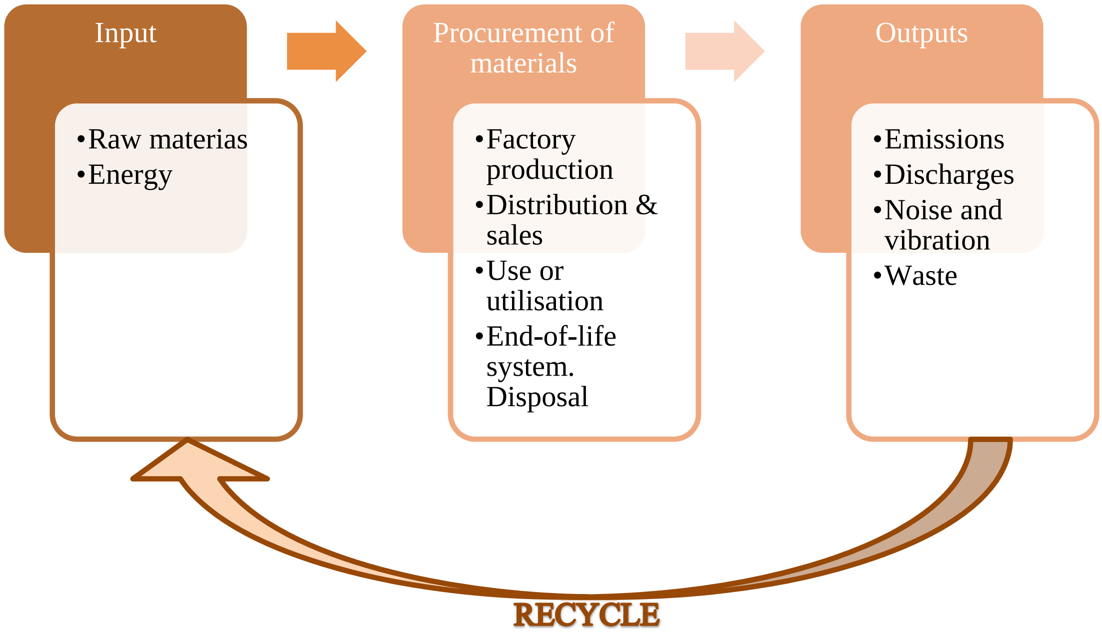

Fig. 1 - The life cycle of a product.

In Spain, around 1.5 million tonnes of domestic plastic, brick, metal and paper/cardboard packaging were recycled in 2019. This figure comes from two main sources of rigorous control to ensure the rigour of the information on waste management; the sources are the municipalities responsible for the selective collection of packaging and the recycling plants responsible for transforming this waste into new raw material. Table 1 shows the recycled packaging waste (in tonnes) by material and area of management (municipal or private) in 2019. The amounts considered have been certified by the local authorities based on the agreements signed by Ecoembes (is a non-profit organization in Spain devoted to sustainable development and recycling).

Quantities recycled (tonnes)	Conventions and Agreements with Public Administrations	Authorised private managers	Total
Plastics	527.949,1	88.786,6	616.735,8
Paper & cardboard	577.319,0	54.364,8	631.683,8
Metals	219.368,2	30.052,0	249.420,1
Wood	0,0	7.821,5	7.821,5
Total	1.324.636,3	181.024,9	1.505.661,2

Table 1 - Amounts recycled in Spain 2019 (source: MITECORD)

Regarding a regional level, Andalusia has 19 light packaging sorting plants and 1,552 Andalusian companies that make the recycling system possible. There are 83,465 yellow and blue containers on public roads, which is 2,046 more than in 2018. In the last five years, the use of the blue bin has increased by an average of 22%. Each citizen deposited 7.5% more paper and cardboard packaging in 2019 compared to the previous year, i.e. each Andalusian citizen deposited 13.2 kg of paper and cardboard per year.

The idea is to predict each container separately, which is more difficult due to the specific characteristics of the state of each container, i.e. its location, the population density of the area in which it is located, the habits of the citizens, etc. And that this prediction serves to subsequently generate optimal collection routes. There are studies to predict waste quantities using time series techniques to predict the quantities of waste generated by an entire city, e.g. Xiamen in China (Xu et al., 2013).

To generate the optimal routing of vehicles, there is still little work directly related to the waste collection problem. There is a study conducted in Portugal, in which collection routes are planned for all days of the month, which are repeated every month and thus minimise the cost of operation. (Teixeira et al.,2004), but it focuses on the routes generated, not on the amount of waste in each container. The objective is to minimise the total distance travelled in the period, which is the sum of the distances travelled by all vehicles on each day.

There is a growing body of literature on the prognosis of the municipal solid waste (MSW) generation. For decades, studies have been conducted using different models, which generally fall into four categories: regression-based models (Daskalopoulos et al., 1998, Sokka et al., 2007, Benitez et al., 2008, Rimaityte et al..., 2012), system dynamics models (Dyson and Chang, 2005, Kollikkathara et al., 2010), computational intelligence models (Jalili and Noori, 2008, Noori et al., 2009, Wang et al., 2010), and time series based models (Chen and Chang, 2000, Navarro-Esbri et al., 2002, Li et al., 2003, Liu and Yu, 2007). Computational intelligence models, such as support vector machines and artificial neural networks, are commonly used due to their high flexibility and non-linear prediction capability. However, these three types of models often use demographic and socio-economic factors that are difficult to identify and quantify (Chen and Chang, 2000; Dyson and Chang, 2005). Time series forecasting models generate future information on MSW generation on a time scale using only historical MSW information.

The authors of this study have previous experience in the use of Artificial Neural Networks (ANNs) in predictive modelling related to transportation engineering and logistics. It is worth highlighting the studies carried out to predict the number of correct inspections at border inspection posts (BIPs). This problem can lead to congestion and bottlenecks within these critical facilities in port or airport systems and can lead to higher costs and delays in the supply chain.

Forecasting of the inspection volume or over freight cargo or maritime traffic can be useful tools to improve the quality of service, operations planning and human resources in ports.

This is also the case of this work where the prediction is about container fill rates and can be useful in the quality of waste collection system (Moscoso-López, J.A et al, 2016; 2020; Ruiz-Aguilar, J.J et al, 2014; 2019; 2020).

Achieving an optimal waste collection will mean an improvement in the service to the citizen, a saving in economic costs for the administration and a significant environmental improvement. The aim is therefore to avoid unnecessary trips to nearly empty containers, as the emissions of pollutants generated by extra trips could harm the environment rather than contribute positively to waste collection.

2. DATA DESCRIPTION

Selective waste management is carried out by the company Aguas y Residuos del Campo de Gibraltar (ARCGISA). It is a public service company owned by the Mancomunidad del Campo de Gibraltar. ARCGISA, as the main company in the agreement for the collection of cardboard, has a limited number of resources to carry out the waste collection. The planning of the current collection system has a wide margin for improvement, as several factors influence in the process, such as the timetables of the staff, the type of vehicle, the type of streets, the situations in the city, the collection timetables, the capacity of the containers themselves, their location, etc. Of the entire collection process, the most important and costly phase of the cycle is the collection procedure, accounting about 70% of the cost associated with waste treatment. This involves the work of many people and vehicles. This project focuses on improving the planning and management of the selective collection of cardboard in the Campo de Gibraltar area.

Campo de Gibraltar consist of seven municipalities, which form one of the three metropolitan areas in the province of Cadiz. In the metropolitan area of the Bay of Algeciras, we find the first industrial pole of Andalusia and the second in Spain and the main port of the national port system in terms of total traffic 5.125.385 TEUS/year . This places the scope of the project at a population of 270,000 inhabitants (INE 2019) and an industrial, commercial and port area of the first national order. It should be noted that Algeciras is the largest municipality in the study area, and is integrated into the National Smart Cities Plan.

In Algeciras, waste collection is currently carried out without predictive analysis. Collection routes are often left to truck drivers. With the growth of cities, the importance of having an efficient waste collection system is increasing. An intelligent waste collection system is therefore proposed to solve the problems faced by the collection services. It will determine which containers need to be collected each day and what is the optimal route for each truck.

The pattern of generation of this waste is fluctuating and does not follow a constant seasonal pattern. This fact makes it difficult to plan the collection, and as mentioned above, it is the operators themselves who manually monitor the filling percentage of the container being collected to estimate when the next collection will take place. This data has to be manually typed in the office, which involves many hours of dedicated staff time. Figure 2 shows the actual annual volume of each container. This is the reason why this project proposes an intelligent system for predicting fill levels based on historical collection data, using predictive analytics and machine learning techniques to estimate which containers are in the optimal range for collection.

3. METHODS

In this work, the objective is to obtain a multiple regression model f:Rn→R for the desired output parameter (the cardboard container volume as a function of the lagged time-series data) using Artificial Neural Networks (ANNs).

3.1 Neural Networks

A Multiple Linear Regression (MLR) model may not be the best fit available. In such cases, a nonlinear regression method like artificial neural networks (ANNs) may provide a better analysis. The most widely used ANN model is the feedforward neural network, based on backpropagation learning procedure (Rumelhart et al., 1986). It models the relationship between X and Y in the form of the equation 1.

$$Y = g\left(\sum_{j=0}^{M} w_{kj} \cdot f\left(\sum_{i=0}^{D} w_{ij} \cdot X_i\right)\right) \tag{1}$$

where *g(x)=x* and *f(x)=tanh(x)*, are proved to be universal approximators (Horni et al, 1988), given the sufficient number of hidden units (M value in the formula). Such networks can, therefore, approximate arbitrarily well any general function, which makes them highly interesting for modelling purposes.

3.2 Experimental Procedure

Thus, the overall system can be viewed as a mapping from a set of input features, to an output variable (the next daily value of cardboard volume in a certain container). The mathematical form of the mapping is determined with the help of the data (training set). Of course, we need to build a system capable of making good predictions on unseen data. In order to measure this generalization capability, crossvalidation using another set of samples (test set) are used.

We adopted crossvalidation to estimate the number of hidden units based on the generalization performance of the model.

We divide available data into 3 distinct groups (training, validation and test sets). Then, we estimate the parameters of each model using one of the groups (the training set). Validation set is used to early stopping and to avoid overfitting. Finally, the test set is then used to test the quality indexes simulating the real performance of the model. This process is repeated 20 times, and the results averaged over these runs. This procedure of resampling simulation has been designed to avoid variation coming from different sources, thus independence and randomness is guaranteed. The different preprocessing methods have been combined with several topologies of backpropagation feedforward neural networks (BPNN) networks.

3.3 Perfomance indexes in classification

To visualise the results obtained with a classification model, the Confusion Matrix (Kohavi and Provost, 1998) is normally used. Each row of the matrix represents the number in actual values for each class and each column represents the number of predictions for each class.

		Prediction	
		Negative	*Positive*
Real	*Negative*	**a**	**b**
	Positive	**c**	**d**

Table 2 - Confusion matrix

True positive and true negative results are a correct classification, while false-negative and false-positive results are two types of errors. It depends on the values:

- **a,** is the correct number of predictions in a negative case.
- **b,** is the number of incorrect predictions in a positive case, i.e. the prediction is positive when the value should be negative.
- **c,** is the number of incorrect predictions that a case is negative, i.e. the prediction is negative when the value really should be positive.
- **d,** is the number of correct predictions that a case is positive.

Some standard indexes are defined: accuracy, precision, true positive rate (TPR), false positive rate (FPR), true negative rate (TNR) and false-negative rate (FNR):

$$\text{Accuracy} = a+d / (a+b+c+d) \quad (2)$$

$$\text{Precision} = d / (b+d) \quad (3)$$

$$\text{Sensitivity} = d / (c+d) \quad (4)$$

$$\text{Specificity} = a/ (a+b) \quad (5)$$

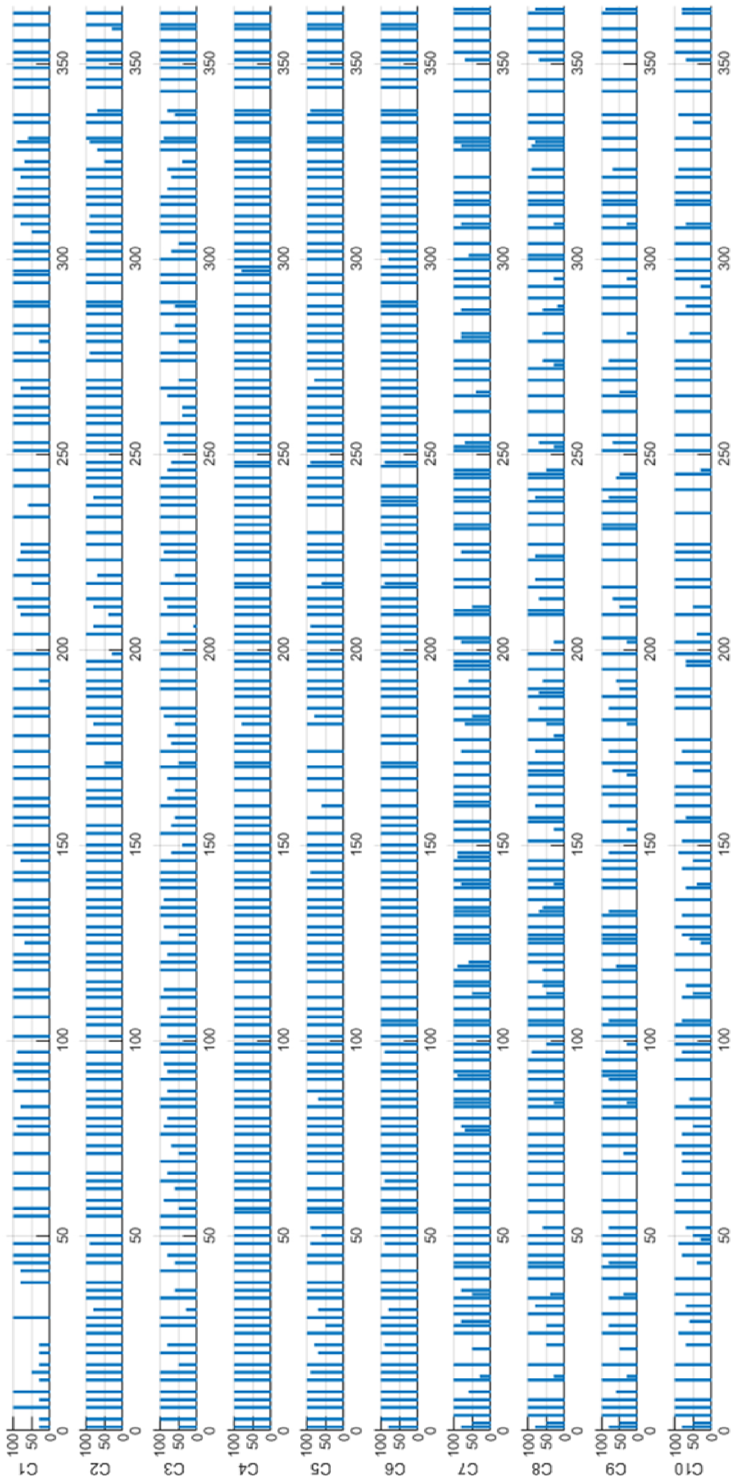

Fig. 2 – Distribution of the actual amount of cardboard collected during the year for each container.

4. RESULTS AND DISCUSSION

This section discusses the most important results obtained in this study. Table 3 shows the real performance of the actual collection system. It is worth mentioning that a lot of inefficiencies were detected. The specificity for each container is really not adequate. This lack of performance means that the actual collection system is very inefficient because there were a lot of times when the truck comes to an empty (or not adequately full) container.

Container	Sensitivity	Specificity	Accuracy	Precision
C1	0,52	0,25	0,4	0,48
C2	0,5	0,05	0,4	0,64
C3	0,61	0,09	0,41	0,53
C4	0,5	0	0,42	0,73
C5	0,51	0,05	0,41	0,65
C6	0,51	0,03	0,42	0,69
C7	0,58	0,16	0,47	0,66
C8	0,57	0,29	0,47	0,59
C9	0,56	0,35	0,47	0,55
C10	0,55	0,33	0,45	0,51

Table 3 - Average performance for each container using the actual collection system.

Table 6 contains the mean correlation coefficients obtained in the random re-sampling experiment with 20 replicates for each container and in function of the number of neurons and the window in the past. The experimental procedure has been applied to a sample of 10 containers of Algeciras, numbered C1-C10. In general, it is worth mentioning that the best performance between the forecasting and the real values were obtained with a certain number of neurons (most of the times, 10 or 20 neurons). This fact indicates that the prediction model is not exactly linear and therefore, methods such as multiple linear regression or ARIMA fails in their predictions. Nevertheless, as Table 6 illustrates, the best results were obtained using a moderate number of neurons and the different number of lags in the past depending on the container. Using too many neurons could improve results in the training stage but can produce overfitting and wrong results in the test phase.

Table 4 compiles the quality indexes of the best models selected in table 6. Especially relevant are the values obtained in sensitivity and specificity because these two indexes indicate how the classifier model works to detect when the cardboard container should be collected (50%-100% of total volume) and also how the truck should not collect a cardboard container (0%-50% of total volume). Both indexes allow us to compare the efficiency of the forecasting model.

There are two cases with two models selected because they have obtained very similar results of forecasting (see Table 4, the case of containers C4 and C8). In these cases, we can adopt two strategies. On the one hand, we can use the Occam’s razor criterium and selecting the simplest model (in this case, with less parameters, i.e. less number of neurons). On the other hand, we can select the model with a lesser distance in the pair (sensitivity, specificity) to the point (1,1). To compare with the actual collection system, we have computed Table 5 reflecting the improvement obtained in each container using the best forecasting model.

Container	Sensitivity	Specificity	Accuracy	Precision	Parameters
C1	0,742	0,910	0,813	0,918	d =3 nhiddens = 10
C2	0,731	0,851	0,760	0,940	d = 4 nhiddens = 10
C3	0,823	0,825	0,824	0,888	d = 2 nhiddens = 10
C4	0,893	0,800	0,877	0,956	d = 5 nhiddens = 5
C4	0,875	0,813	0,864	0,959	d = 5 nhiddens = 10
C5	0,721	0,975	0,780	0,990	d = 1 nhiddens = 50
C 6	0,885	0,800	0,868	0,947	d = 4 nhiddens = 10
C7	0,902	0,514	0,800	0,839	d = 2 nhiddens = 20
C8	0,790	0,825	0,802	0,893	d = 2 nhiddens = 20
C8	0,781	0,842	0,803	0,901	d = 2 nhiddens = 50
C9	0,781	0,845	0,807	0,881	d = 4 nhiddens = 20
C10	0,748	0,914	0,821	0,920	d = 5 nhiddens = 50

Table 4. – Mean ANN best model's parameters for each container.

Container	Sensitivity	Specificity	Accuracy	Precision	Parameters
C1	0,222	0,66	0,413	0,438	d =3 nhiddens = 10
C2	0,231	0,801	0,36	0,3	d = 4 nhiddens = 10
C3	0,213	0,735	0,414	0,358	d = 2 nhiddens = 10
C4	0,393	0,8	0,457	0,226	d = 5 nhiddens = 5
C5	0,211	0,925	0,37	0,34	d = 1 nhiddens = 50
C 6	0,375	0,77	0,448	0,257	d = 4 nhiddens = 10
C7	0,322	0,354	0,33	0,179	d = 2 nhiddens = 20
C8	0,22	0,535	0,332	0,303	d = 2 nhiddens = 20
C9	0,221	0,495	0,337	0,331	d = 4 nhiddens = 20
C10	0,198	0,584	0,371	0,41	d = 5 nhiddens = 50
Mean Total	**0,26**	**0,67**	**0,38**	**0,31**	

Table 5. – Improvements obtained using the best forecasting model for each container.

C1		nhiddens				
		1	5	10	20	50
lags	1	0,496	0,810	0,824	0,829	0,839
	2	0,352	0,849	0,851	0,856	0,790
	3	0,320	0,820	**0,859**	0,855	0,822
	4	0,320	0,787	0,848	0,855	0,818
	5	0,324	0,803	0,845	0,851	0,774
	6	0,303	0,788	0,850	0,826	0,806
	7	0,242	0,729	0,757	0,851	0,791

C2		nhiddens				
		1	5	10	20	50
lags	1	0,386	0,844	0,840	0,875	0,877
	2	0,504	0,868	0,875	0,874	0,853
	3	0,561	0,857	0,886	0,871	0,898
	4	0,548	0,869	**0,906**	0,898	0,834
	5	0,457	0,881	0,850	0,881	0,843
	6	0,592	0,879	0,893	0,883	0,834
	7	0,640	0,871	0,890	0,880	0,832

C3		nhiddens				
		1	5	10	20	50
lags	1	0,413	0,721	0,731	0,807	0,802
	2	0,394	0,786	**0,842**	0,850	0,827
	3	0,362	0,810	0,813	0,808	0,764
	4	0,422	0,820	0,760	0,792	0,763
	5	0,499	0,754	0,810	0,788	0,738
	6	0,457	0,754	0,775	0,786	0,734
	7	0,558	0,748	0,753	0,779	0,756

C4		nhiddens				
		1	5	10	20	50
lags	1	0,666	0,912	0,912	0,910	0,899
	2	0,614	0,924	0,911	0,914	0,918
	3	0,801	0,902	0,900	0,897	0,903
	4	0,738	0,935	**0,936**	0,903	0,856
	5	0,575	**0,936**	0,907	0,905	0,880
	6	0,680	0,903	0,917	0,931	0,913
	7	0,737	0,927	0,923	0,905	0,919

C5		nhiddens				
		1	5	10	20	50
lags	1	0,276	0,792	0,869	0,887	**0,901**
	2	0,433	0,858	0,878	0,895	0,837
	3	0,581	0,859	0,868	0,854	0,862
	4	0,506	0,839	0,852	0,868	0,810
	5	0,579	0,856	0,868	0,872	0,753
	6	0,597	0,775	0,866	0,833	0,787
	7	0,557	0,837	0,823	0,861	0,792

C6		nhiddens				
		1	5	10	20	50
lags	1	0,590	0,862	0,872	0,873	0,875
	2	0,520	0,890	0,891	0,900	0,894
	3	0,599	0,890	0,887	0,889	0,855
	4	0,578	0,876	**0,903**	0,898	0,881
	5	0,719	0,891	0,881	0,898	0,809
	6	0,589	0,855	0,885	0,891	0,815
	7	0,594	0,870	0,892	0,853	0,804

C7		nhiddens				
		1	5	10	20	50
lags	1	0,208	0,577	0,591	0,619	0,614
	2	0,307	0,571	0,637	**0,667**	0,636
	3	0,207	0,549	0,606	0,650	0,618
	4	0,383	0,611	0,598	0,618	0,559
	5	0,321	0,568	0,624	0,654	0,583
	6	0,303	0,470	0,633	0,577	0,580
	7	0,214	0,422	0,434	0,561	0,586

C8		nhiddens				
		1	5	10	20	50
lags	1	0,320	0,627	0,645	0,676	0,669
	2	0,321	0,635	0,659	**0,682**	**0,682**
	3	0,290	0,627	0,659	0,621	0,548
	4	0,284	0,588	0,624	0,672	0,624
	5	0,186	0,641	0,666	0,670	0,593
	6	0,234	0,482	0,586	0,639	0,540
	7	0,209	0,581	0,626	0,607	0,507

C9		nhiddens				
		1	5	10	20	50
lags	1	0,298	0,665	0,674	0,705	0,706
	2	0,307	0,667	0,696	0,715	0,712
	3	0,325	0,668	0,697	0,710	0,661
	4	0,281	0,689	0,671	**0,720**	0,677
	5	0,263	0,699	0,691	0,719	0,649
	6	0,197	0,596	0,687	0,706	0,657
	7	0,242	0,518	0,640	0,617	0,564

C10		nhiddens				
		1	5	10	20	50
lags	1	0,324	0,646	0,664	0,710	0,707
	2	0,270	0,684	0,691	0,713	**0,729**
	3	0,254	0,630	0,683	0,710	0,678
	4	0,278	0,658	0,671	0,686	0,606
	5	0,134	0,632	0,651	0,681	0,637
	6	0,249	0,507	0,656	0,659	0,590
	7	0,178	0,587	0,623	0,645	0,580

Table 6. - Mean correlation coefficients in the random re-sampling experiment with 20 replicates for each container as a function of the number of neurons and the window in the past.

5. CONCLUSIONS

In summary, with the experiments done, the R correlation coefficient (over test sets in the best models) yields closer estimates to real values of the collected year 2019 time-series. It was clear from our experiments that some of the neural models are much better than others (see Table 4). For example, the R correlation coefficient (average) between BPNN best model (nhiddens = 10, d = 4) is 0.936 in the container C4, better than the rest of models (over test sets).

We have tested the potential of shallow ANNs as a predictive tool in this application. ANNs require no priori assumptions about the model in terms of mathematical relationships or data distribution. We have used multilayer perceptron models (MLPs) with a backpropagation learning rule. The designed procedure of resampling simulation avoid variation, thus independence and randomness is guaranteed. Determination of the model which fits better the prediction of each cardboard container volume time-series can be possible. The improvements in the performance indexes have been quite relevant and the new predictive system should be easily applied to save costs and fuel, thereby reducing emissions and contributing to environmental sustainability.

In summary, this work provides an effective and alternative way to compute predictions with the hypotheses used in the study, obtaining a new forecasting system that allows us to improve efficiency and it should be useful to better garbage collection planning.

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