Household Packaging Waste Management

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Abstract. Household packaging waste (HPW) has an important environmental impact and economic relevance. Thus there are networks of collection points (named "*ecopontos*" in Portugal) where HPW may be deposited for collection by waste management companies.
In order to optimize HPW logistics, accurate estimates of the waste generation rates are needed to calculate the number of collections required for each *ecoponto* in a given period of time.
The most important factors to estimate HPW generation rates are linked to the characteristics of the population and the social and economic activities around each *ecoponto* location.
We developed multiple linear regression models and artificial neural networks models to forecast the number of collections per year required for each location. For operational short term planning purposes, these forecasts need to be adjusted for seasonality in order to determine the required number of collections for the relevant planning period. In this paper we describe the methodology used to obtain these forecasts.

Keywords: Forecasting, Household Packaging Waste, Waste Collection, Recycling, Seasonality.

1 Introduction

Recycling of waste materials became a very important issue for society, as the environment benefits greatly from any advances made in direction of a cleaner future. Process collecting for recycling involves teams of workers and vehicles. One of the main problems lies in finding optimal collection routes, where a set of collection points is targeted, and each point is given a priority level. This problem can be described as the Vehicle Routing Problem (VRP). However more flexibility is needed when it comes to choose only a part of the collection points to be visited, instead of the whole set. Thus, a more fitting description of the selective waste collection process may be the Team Orienteering Problem (TOP).
In this context, the TOP can be described as the problem of designing the routes to be assigned to a fleet of vehicles that perform the collection of different types of waste stored along a network of collection points. Each one of these collection points contains

a certain amount of waste that is directly linked to the respective priority level. The collection routes have maximum durations or distances, and consequently, the selection of collection points to be visited by the vehicles is made by balancing their priorities and their contributions for the route duration or distance. The objective is to maximize the total amount of waste collected by all routes while respecting the time or distance constraints.

Aside from the routing problem, there are other issues related to the process of waste collection for recycling, especially when dealing with real scenarios and the activity of real waste collection companies. One of these issues is the estimate of waste material quantities generated over time at each collection point in a given collection network, which enables the estimation of a waste generation rate (WGR) for each collection point. Estimating WGRs is crucial for designing collection networks since collection points are located according to these estimates. Moreover, forecasts for waste generated along a network are used to design collection routes as each collection point is given a priority according to their WGR, which translates into the frequency of service by collection vehicles.

Considering the goals Portugal has to fulfil for the recycling and recovery of HPW, there is a permanent need for increased efficiency in waste collection. Thus, one important task is the development of models to forecast the quantities of waste generated at collection points.

The paper is structured in 6 sections. Section 2 presents the problem. A literature review is presented in section 3. The forecasting models developed are described in section 4. Seasonal adjustments to the base forecasts are described in section 5. Finally, in section 6, the results and main conclusions of this study are presented.

2 The Problem

The main objective is to solve a real-world problem faced by an intermunicipal waste management company, in six municipalities: Braga, Vieira do Minho, Vila Verde, Povoa do Lanhoso, Amares and Terras de Bouro, in Northern of Portugal (Fig. 1).

Fig. 1. Collection area of HPW

The problem focus is on HPW collection, and a major step to achieve a good performance is to obtain accurate forecasts for waste generation rates at the waste collection points in order to determine the frequency of collection.

In Portugal, household packaging waste (HPW) is disposed of in collection points called *ecopontos*. Each *ecoponto* can have three types of containers, identified with different colors: glass (green), paper/cardboard (blue), and plastic/metal (yellow), as can be seen in Fig. 2.

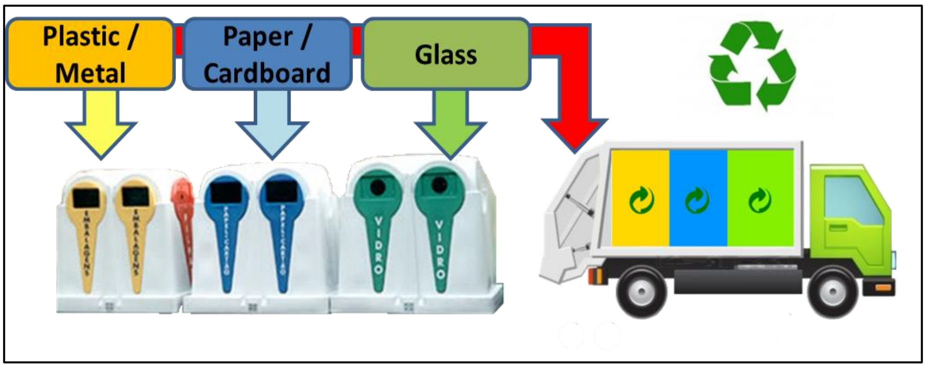

Fig. 2. *Ecopontos* illustration

The company currently operates a network of more than 1,200 *ecopontos* located across. These six municipalities are characterized by a mix of urban and rural areas, which require different strategies concerning waste management.

The company vehicles do not visit all *ecopontos* every workday. It is necessary to select a subset of *ecopontos* to visit, according to their estimated fill rate, each time the route planning is done. Thus, given a planning horizon, for example a week, the company must decide which *ecopontos* must be visited (because they are near full) and which can be skipped (because they are near empty) by the collection fleet in order to design efficient routes for the selective collection of HPW. Thus the priority level of an *ecoponto* is highly related to the estimated amount of waste it holds during the route planning phase, Fig. 3.

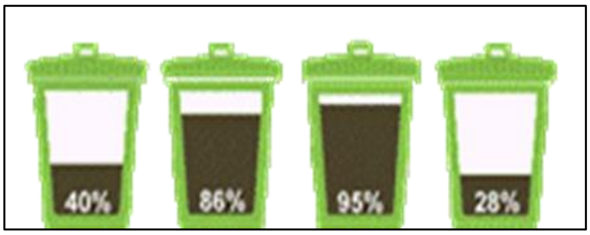

Fig. 3. Estimated amount of waste held

Taking into account its priority level, an *ecoponto* may or may not be selected to be visited during the established planning horizon, Fig. 4.

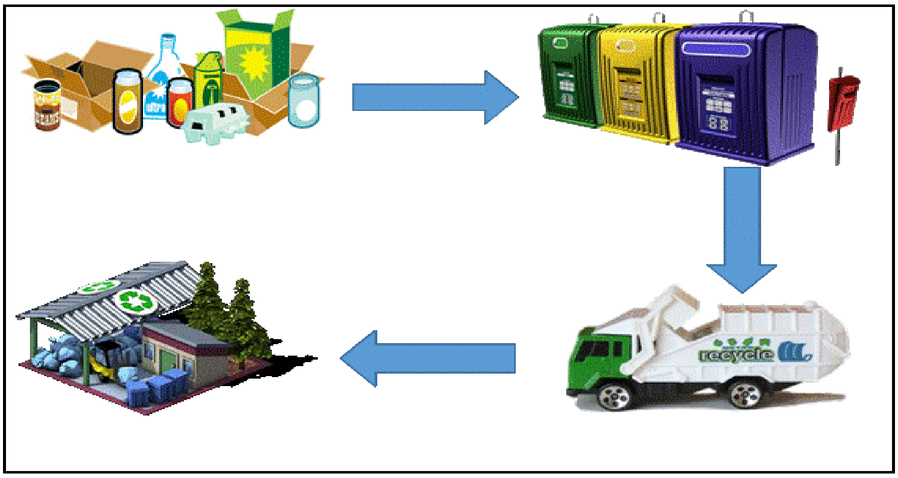

Fig. 4. House Packaging Waste Collection for Recycling

Thus, to improve route planning, reliable forecasts of the amount of waste generated at each *ecoponto* are necessary. In a previous phase of this study [5], significant factors for HPW generation rates were identified in order to develop forecasting models to predict the number of times each *ecoponto* should be visited during a certain period of time. However, due to a variety of seasonal factors, such as holidays, periodic events, weather conditions, etc., waste generation rates need to be seasonally adjusted. For example, the number of collection visits required in this study increases significantly during summer months. In this paper we present a method for making these seasonal adjustments that allow a significant reduction of the number of unnecessary visits to ”nearly empty” *ecopontos* and therefore saving resources and reducing the logistics costs of the operation, Fig. 5.

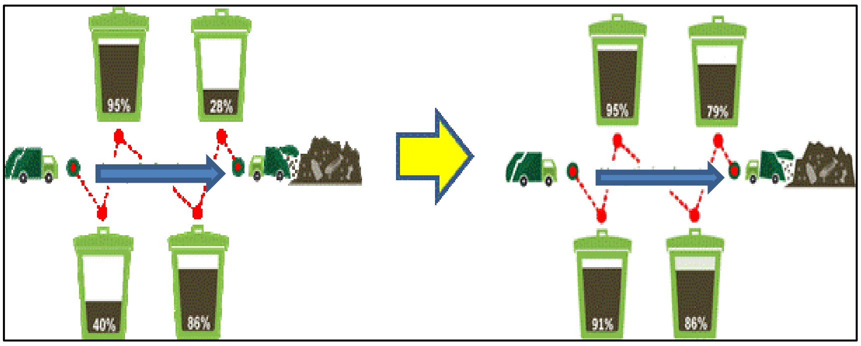

Fig. 5. Optimizing collection routes

3 Literature Review

Forecasting the generation rates of municipal solid waste (MSW) is important for both, the development of waste management infrastructures, and the implementation of the logistics processes for waste collection.

In a review, Beigl et al. [2] concluded that MSW generation is best predicted by time series analysis and regression methods. According to Denafas et al. [4] seasonal factors may have a strong impact on MSW generation and should be taken into account in the decision-making processes concerning waste management. Concerning waste generation contributing factors, Wang and Nie [11] identified the growth of urban population and gross domestic product (GDP) as the most important ones. Grossman et al. [6] considered factors such as: increase of population, income level and housing type. Later studies pointed out that waste generation can be related to production and consumption levels [3, 9]. More detailed analyses showed that the growth of the urban population had a greater impact than GDP on the total amount of MSW produced. Also, with factors like increasing income, MSW seems to change more in composition rather than in total amount generated. Other factors that may influence the generation and composition of waste are climate, living habits, level of education, religious and cultural beliefs, and social and public attitudes [1, 8, 10].

Frequently, time series forecasting models may be a good choice to estimate MSW generation when there is access to a substantial amount of historical data. Based on the comparison of several forecasting methods, Beigl et al. [2] imply that a forecasting tool based on socio-economic variables was more suitable than single time series analyses. In most cases, the application of modelling methods such as regression analyses, and group comparisons, seems to be the best option when the goal is to test the relationship between the level of affluence and the generation of total MSW or a material-related fraction, and to identify significant effects of waste management activities on recycling quotas. The application of time series analyses and input-output analyses is advantageous when there is a need for special information (i.e., assessment of seasonal effects for short-term forecasts).

After this review, it became clear that most of the previous research in this area focused on a different level of analysis that did not match our purpose of predicting waste generation at each collection point in order to determine when it needs to be emptied.

4 Forecasting Models

The available data consisted on all the waste collections performed by the company in all the six municipalities it operates from 2013. It contained monthly records showing how many times each *ecoponto* in the network was emptied during each month of the year.

Our aim was to forecast the number of times each *ecoponto* needs to be emptied each year. Therefore, this number of collections per year (and per *ecoponto*), hereafter referred as CPY, was set as the dependent variable considered in the forecasting models developed. In the next subsections, a brief description of the developed models is given, followed by a detailed description of the seasonal adjustments made to estimate the required number of collections per month.

The forecasting models for CPY use data from waste collection records. The factors used to estimate waste generation rates, were determined using several sources for demographic information and socioeconomic indicators. In Table 1, a list with all explaining factors for HPW generation is presented.

Table 1. Factors used to estimate waste generation rates.

Factor	Description	Acronym
1	Number of E*copontos* in the area	NE
2	Population Density in the area	PD
3	Number of Inhabitants per E*coponto*	NRE
4	*Ecoponto* Density	ED
5	*Ecoponto* Type (street level or underground) – qualitative	ET
6	*Ecoponto* Position (closed or open area) – qualitative	EP
7	*Ecoponto* Capacity	EC
8	Number of *Ecopontos* within a 300 meters radius	NE300
9	Demographic Factor (household density around each *ecoponto* in a 300 meter radius) - qualitative	DF
10	SocioEconomic Factor (based on the number of schools, businesses, local attractions, leisure and sports infrastructures, restaurants, etc.)	SEF

The data used consisted of information on these factors for all the *ecopontos* (185) from two municipalities: Amares and Vila Verde.

We used two different methods to develop the forecasting models: Multiple Regression (MR) and Artificial Neural Networks (ANN). MR models were developed using *Forecast Pro* software and ANN models were developed using *Encog* [7]. Regression models are widely known and used for forecasting purposes, and ANN are attaining more recently some relevance in this field, with promising results being reported in the last years.

The best performing forecasting models for the collection of cardboard at the 185 *ecopontos* sample are described in equation 1 (regression model) and Table 2 (ANN model).

$$CPYi = 18.209DF - 0.006EC + 8.314ED + 21.141ET + 0.035NRE - 0.027PD + \epsilon \quad (1)$$

Table 2. Artificial Neural Network model.

Network Type	Multilayer Perceptron
Network Structure	3 layers (4-4-1)
Learning algorithm	Levenberg-Marquardt
Activation function	Sigmoid
Training, Test, Validation	125, 10, 50
Training Epochs	1000
Inputs	DF, ET, NE, SEF
Output	CPY

The performance of these models at forecasting the actual number of collections per year (Observed collections) in a test sample of 50 *ecopontos* can be seen in Fig. 6.

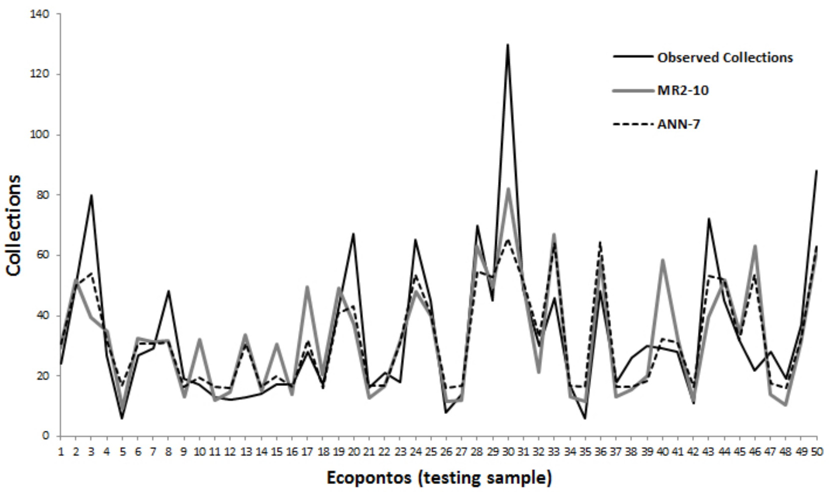

Fig. 6. Forecast results for the best ANN and regression models.

The mean absolute deviation (MAD) of forecasting errors for both models is shown in Table 3.

Table 3. Mean Absolute Deviation of Forecasting Errors.

Multiple Regression	Artificial Neural Network
10.44	9.14

5 Seasonal Adjustments

The models described in section 4 are used to estimate the number of collections per year required for each *ecoponto*. However, as previously stated, there are seasonal variations on the waste generation rates (WGRs). Therefore there is a need to adjust the number of collections to these variations in order to forecast the number of collections required for each month of the year. For example, in summer months, there are usually higher WGRs in this region due to emigrants returning to their home country and tourism activities resulting in significant population increases. There are also seasonal changes in social habits. For example, there is a higher consumption of beverages in plastic, metal and glass containers. Many other factors may also have contributed for seasonal variations in WGRs throughout the year.
Table 4 shows general performance indicators of the company operation from 2010 to 2014. In order to describe the seasonal adjustment procedures we will use data concerning cardboard collection in a sample of 185 *ecopontos* from two municipalities, Amares and Vila Verde. Table 5 shows the average monthly number of effective cardboard collections done for the 185 *ecopontos* in the sample.

Table 4. Company indicators

Year	2010	2011	2012	2013	2014
Collections	129 908	143 166	142 352	143 089	136 357
Glass	11 570	11 555	11 238	11 829	11 887
Cardboard	62 294	72 431	70 234	69 704	65 571
Plastic	56 044	59 180	60 880	61 556	58 899
Quantity Coll.					
Glass (ton)	6 320	6 282	5 968	6 224	6 170
Cardboard (ton)	7 137	7 151	6 244	6 245	6 354
Plastic (ton)	1 434	1 730	1 909	1 992	2 095
Number of *Ecopontos*	1 131	1 170	1 208	1 114	1 159

Table 5. Average number of cardboard collections per month.

Month	January	February	March	April	May	June	July	August	September	October	November	December
Number of Collections	754	719	617	783	783	677	909	828	868	769	775	793

The analysis of the data in Table 4 shows that there is not any significant trend in the number of collections from 2010 to 2014. Thus to determine the seasonal factors we may simply divide the average number of collections for each particular month by the monthly collections average. Table 6 shows the seasonal factors for each month of the year.

Table 6. Seasonal factors

Month	January	February	March	April	May	June	July	August	September	October	November	December
Seasonal Factor	0.976	0.930	0.798	1.013	1.013	0.876	1.176	1.071	1.123	0.995	1.003	1.026

Once determined the seasonal adjustment factors, the forecasts of total collections for each month can be corrected using the corresponding seasonal adjustment factor. For example, if the forecast of CPY_i for a certain *ecoponto* i is 120, then the average number of collections per month will be 10. To correct forecasts for example for the months of March and July, the factors 0.798 and 1.176 are used. Thus the revised forecast for required collections for *ecoponto* i would be 8 collections for March and 12 collections for July. Since the company operates approximately 25 days per month (there is no collection on Sundays), in operational terms this means that *ecoponto* i should be emptied every 3 days in March and every 2 days in July. The use of these revised forecasts at the route planning phase makes the collection routes much more efficient by avoiding visits to “nearly empty” *ecopontos*.

6 Discussion and Conclusions

The use of the seasonal adjustments resulted in an important reduction of the errors at forecasting the number of effective collections required per month. The impact of the revised forecast values resulted in an estimated 10% decrease in the number of visits to *ecopontos* not resulting in any collection. For the company involved in this study this means avoiding hundreds of unnecessary visits to *ecopontos* per year, Fig. 7.

Fig. 7. House Packaging Waste Collection for Recycling

In this study we presented a real-world problem faced by a company that collects House Packaging Waste (HPW) deposited in a network of waste collection points (*ecopontos*). The main problem faced by the company was the high number of visits made by the collection teams to *ecopontos* that are "empty". This represented an important waste of resources that translated in thousands of kilometers traveled and hours spent by the collection teams that do not resulted in any collection.

Our main goal was to improve the forecasts for the number of monthly waste collections required. We achieved this by correcting the base forecasts for the number of waste collections per year for each *ecoponto* (CPYi), developed with Regression and Artificial Neural Networks models, using seasonal factors for each month of the year.

These seasonal factors where determined using actual data from effective collections. The results achieved show that these seasonal adjustments reduce the number of unnecessary visits to *ecopontos*, thus leading to important savings in environmental and logistics costs.

Acknowledgments

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