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A Model for Assessing Waste Generation Factors and Forecasting Waste Generation using Artificial Neural Networks: A Case Study of Chile

Eduardo Ordóñez-Ponce, M.E. (Nat Res) Student ordonez@lincoln.ac.nz
Sandhya Samarasinghe, Ph.D. sandhya@lincoln.ac.nz
Lynn Torgerson, B.E. torgersl@lincoln.ac.nz
Natural Resources Engineering Group, Environment, Society and Design Division,
Lincoln University, P.O. Box 84, Canterbury
New Zealand

Abstract: One of the bottlenecks in the implementation of waste management policies in Chile is the lack of information on factors contributing to waste generation. Recognising these factors is essential for implementing waste management policies to reduce the amounts of waste generation. Population, Percentage of Urban Population, Years of Education, Number of Libraries, and Number of Indigent People were identified as the most important factors representing socio-economic conditions contributing to waste generation, all contributing positively. Using these variables, communes were clustered into three groups from which representative communes were selected for data collection for forecasting quantities of waste. Artificial Neural Networks were used for identifying important factors, clustering communes and forecasting waste generation. The model is designed to represent most of the communes of a country. In this case study, the best possible scenario represents up to 67.3% of the communes, based on the representativeness of each selected representative. However, due to lack of information, this rate is reduced to 48.8%. Forecasted rates show that represented communes will generate 100, 240 and 2,900 tonnes/month, respectively, with the yearly generation rate decreasing to –1% by 2010.

Introduction

Chile's current constitution (1980) guarantees the right of every citizen to live in a pollution-free environment. The Government is in charged with the role of safeguarding this right while protecting and preserving nature [1]. In 1994 the Environmental Act was passed, establishing the first direct relationship between the state and the environment. However, authorities have found technical and economic barriers to implementing the law, as well as opposition from various interest groups.

The first Policy on Integrated Management of Domiciliary Solid Residues (DSR) was formulated in 1997. The aim of the policy was to minimise the environmental impact of DSR and eliminate negative effects on public health. A few Municipalities[i] started recycling programmes, incorporating a limited number of voluntary households for short periods of time. By 2001, 9.5% of DSR were recycled in Chile [2], and the Metropolitan Region (MR)[ii], generator of 52.2% of the country's total residues, recycled 7% [3].

The amount of waste generated in Chile has had a dramatic increase over the last decade. Figure 1 shows that in the period 1996-2002 the total amount of waste generation rose 67.0% (with the regions II, IV, VII and XII increasing more than 100%). However, Population, a variable widely supported as a waste generation factor, rose just 4.84%, with two regions (III, XII) even experiencing a negative growth.

With the aim of improving above figures, CONAMA established the Environmental Agenda for the period 2002-2006 setting a goal of disposing 80% of domiciliary waste in landfills by 2005 and a recycling rate of 20% by 2006 [4].

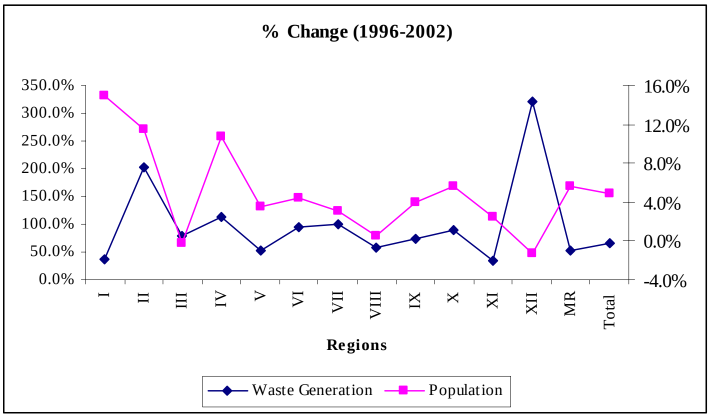

Figure 1: Regional waste generation and population percentage change between 1996 and 2002

Aim

The main aim of the research described in this paper is to contribute to the development of sensible waste management practices and the improvement of the management of DSR in Chile, using information on quantity of waste and waste generating factors. The aim is to be achieved by designing a communal analysis tool to study waste generating factors and to forecast waste generation levels.

Background

Past researchers have focussed on different variables, but population and income are the most considered, although with inconclusive results as to the relevance to waste generation. Among some of the variables considered are: household size, residency type, age groups, employment, electricity consumption, tipping fees, CPI, GDP, education, culture, geography and climate.

Population has been considered to be one of the most important variables affecting waste generation [9,10]. However, it has also been found to be of little statistical significance predicting average waste generation rate [11]. Income has also been found to be one of the most influential factors affecting waste generation [12,13,11]. Nevertheless, others have observed no influence of income on waste [14].

In developing relationships between variables and waste generation, most of the researchers have used regression analysis and time-series models for predicting waste generation. In 1972, Shell and Schape's regression analysis revealed that the number of stops [which we believe to be stops for purchasing consumables] was the most significant variable, followed by number of families and single-building dwelling units. The model did not clarify the significance of the variables [15]. In 1974, Grossman et al.'s regression model neither explained nor forecasted waste generation, concluding that waste production occurred independently of the analysed variables and that these were not significant for the assessed community [16]. Ali Khan and Burney (1989) mixed different cities around the world to generate a single explanatory model; however, this approach cannot be justified due to contrasting waste generating conditions in different countries. They concluded that income, temperature and dwelling occupancy rate affected the percentage of waste components [12]. McBean and Fortin (1993) developed two models. One model predicted types of materials, but showed large variations in the predictions due to population growth and did not consider the dynamic interactions between waste generation rate and economic activity. The other model, a better predictor of total waste, did not predict waste components [9]. Buenrostro et al. (2001) worked with monthly income and number of dwellers per household, but the study concluded that these variables were of limited value in explaining solid waste generation. Moreover, the data collection period was limited to spring [13]. Bagby et al. (2001) developed models as part of Seattle's Solid Waste Plan. They found little growth in waste generation over the forecasted period due to Seattle's characteristics such as a continuing decline in the average household size and trends in the housing markets. As the model has been designed specifically to Seattle, it is not transferable to other places [17].

Some researchers have worked with Time-Series with better results. In 1986, Bridgwater made projections for up to fifty years, concluding that S-curves give the best results. Bridgwater's model assumed continuity of social, economic and technical trends [18]. In 1993, Chang et al. used geometric lag time-series analysis for the period 1981-1990 and found a negative relationship between average waste generation per capita per day and total population, a relationship affected by a period of population mobilisation [11]. Bruvoll and Ibenholt (1997) developed an economic model for forecasting manufacturing industries' waste generation in Norway. They concluded that, despite technological progress, an increase in waste exceeds growth in production and in the GDP. This model was subject to assumptions such as demand equals supply, firms behave competitively and constant returns to scale technology [19]. Chang and Lin (1997) applied an ARIMA (Auto Regressive Integrated Moving Average) model to time-series data for 12 districts of Taipei City, Taiwan, from 1990 to 1995, with predictions solely based on previous trends in waste generation. They found that recycling is important in the prediction of waste [20]. Finally, Navarro-Esbrí et al. (2002) analysed waste generation using sARIMA (seasonal ARIMA) and a non-linear technique and concluded that both methods give good results in terms of predictive accuracy and cumulative errors. However, the key to this analysis is the selection of the appropriate dimensionality of municipal solid waste as a dynamic system and the use of differential mathematical functions of the generating model [21]. Koushki and Al-Khaleefi's (1998) research on waste prediction in Kuwait related household's solid waste generation to monthly income, family size or to the number of persons employed per household. They concluded that any one of these three variables can forecast waste generation [22]. Chen and Chang (2000) developed a grey fuzzy dynamic model for the prediction of solid waste generation in the city of Tainan, Taiwan. The model is a good predictor of waste generation for the case of Tainan in the cited period of fourteen years. Nevertheless, the model depended on an extensive database [23].

Artificial Neural Networks

Artificial Neural Networks (ANNs) are simplified computational models of the brain [24]. They attempt to emulate some of the functions of the brain such as learning from experience and the capability of solving problems by using, modifying and extrapolating acquired knowledge. ANNs are capable of classifying patterns, clustering, approximating functions, forecasting, optimising results and controlling inputs such that a system follows a desired trajectory [25].

An ANN is formed by a large number of processing neurons interconnected by weights, which represent the influence of one neuron on another. ANNs have been classified into feed forward and recurrent networks. In a feed forward network, neurons are grouped into layers and the signals flow from one layer to another in the forward direction. Multi Layer Perceptron (MLP) networks are feed forward networks (Figure 2 (a)). A typical MLP network consists of an input layer, a hidden neuron layer and an output layer of neurons. Input layer simply transmits inputs through weights to hidden neurons where weighted inputs are accumulated and processed by a transfer function to generate an output to be sent to the output layer. A similar process takes place in the neurons in the output layer where outputs are generated. In a recurrent network the flow is forward and backwards. In recurrent nets for time series forecasting, outputs of some neurons are fed back to the same or other neurons in preceding layers. For example, in SOFMs (Figure 2 (b)), the input layer transmits data to the output layer neurons that feed their output back to the neurons in the same layer. The Elman and the Jordan nets are examples of recurrent networks (Figure 2 (c) and (d)). In Elman networks, hidden layer outputs are fed back to the input layer for processing in the next time step and in Jordan network, output layer output is fed back to the input layer. This feedback helps incorporate temporal effects into recurrent networks.

ANNs are modelled via a learning process which can be supervised or unsupervised. In supervised learning, the network is presented with the inputs and target outputs iteratively and the network adjusts its weights using efficient learning methods such as steepest descent. The aim is to minimise the error by generating outputs as close as possible to the targets. Examples of supervised networks are MLP and Recurrent Networks. Conversely, unsupervised learning uses no external supervision and clusters the data presented to the network based on the properties of the data in a self-organising manner. An example where unsupervised learning is used is SOFM. As shown in Figure 2 (b), multidimensional data are projected onto a 2-dimensional map where similar input vectors form clusters in the course of learning.

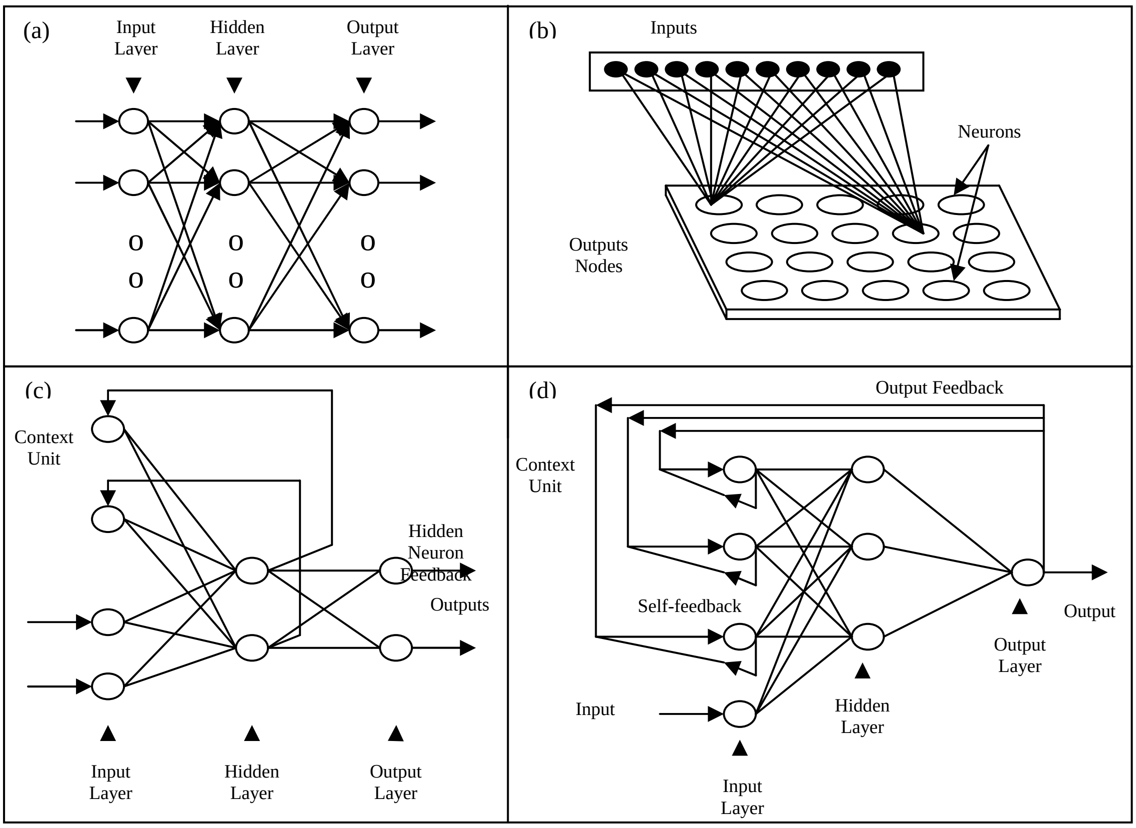

Figure 2: Types of Artificial Neural Networks. (a) Multi-Layer Perceptron (MLP), (b) Self-Organising Feature Map (SOFM), (c) Elman Recurrent Network, (d) Jordan Recurrent Network.

In this research, the relationship of the selected variables with waste generation is developed using an MLP, SOFM are used for clustering of communes, and waste forecasting models are developed using MLP and recurrent networks. The software used is NeuroShell 2 by Ward Systems Group®, Inc.
The dataset is divided into three distinct sets. The training set is used to train the network, the testing set is used to assess the model at various stages of training and the validation set is used to test the model predictions on unseen data (generalisation). In the evaluation process, the best networks are selected based on the highest coefficient of multiple determination (R^2) and the lowest mean squares error (MSE).
Neural networks is a relatively new research field and is rapidly growing in popularity as evidenced by the proliferation of neural networks applications in virtually all fields of research. Their flexible and adaptive nature makes them very powerful predictors and classifiers and enable them to model any non-linear function to any degree of accuracy [26].

Research Method

- ***Stage 1: Determining Waste Generating Factors***

This involved several steps at the end of which factors that have a significant effect on waste generation are determined. Based on the literature review, possible waste generating factors were evaluated and a preliminary set of relevant variables selected.
Global Variables: While past literature points to inconclusive results, a set of variables was identified as possible indicators. *Population indicators*: Population, Percentage of Urban Population, Population Density, Gender, Age Groups and Native Population. *Economic indicators*: Poverty Level and Income per Household, Economic Activities, Regional GDP, Foreign Investment, Exports, Construction Rate, Vehicles, Employment, Labour Force and Unemployment. *Education indicators*: Years of Education, Cultural Activities, Number of Public Libraries and Illiteracy Rate. *Dwelling indicators*: Number of

Houses and Households and Number of People per Household. *Geographic indicators*: Geography and Climate. *Waste-related indicators*: Waste Generation, Waste Generation Rate, Per Capita Waste Generation and Existence of Disposal Sites.

Data Collection: Data on global variables was sourced from a number of locations in Chile such as the Central Bank of Chile, the National Institute of Statistics (INE), the National Commission for the Environment (CONAMA) and relevant Ministries.

Data Processing: Data was processed searching for multicollinearity and heteroskedasticity. A multicollinearity analysis showed that Waste Generation is highly correlated with Urban Population, Gender, Population, Non-Poor Population, Number of Houses, Age Group and Number of Vehicles. These variables are also highly correlated with each other, thus only one of them can be included in the model. Therefore, variables with high correlation with the dependent variable and low correlation with the other independent variables were selected.

In order to select the most appropriate variables, different sets of variables were created using one of the highly correlated variables (Population, Urban Population, Males, Females, Non-Poor Population, or People between 25 and 44 years of age). The other variables included were Percentage of Urban Population, Years of Education, Number of Libraries, Indigent Population and Poor Non-Indigent Population. The Breusch and Pagan test detected heteroskedasticity in all the sets. However, its effect was reduced using the Two-Step Weighted Least Square method. The final selected explanatory variables were Population (POP), Percentage of Urban Population (PUP), Years of Education (EDU), Number of Libraries (LIB) and Indigent Population (IND).

Table 1 shows that all the explanatory variables are highly correlated to Waste Generation (WG). Correlations between per capita waste generation (PCWG) and the other variables were also tested and they showed that PCWG very poorly correlates with all the variables including WG. Table 1 also shows that the selected explanatory variables are more correlated to Population than to Waste, highlighting the importance of Population. However, Population by itself could not cluster the communes in an appropriate manner to analyse waste generation in Chile. In fact, it was found that communes with similar population but different levels of urban population, education, number of libraries or indigent people, did not generate similar amounts of waste [27].

Table 1: Correlations Table

	POP	PUP	EDU	LIB	IND	PCWG
WG	0.875	0.502	0.519	0.522	0.503	0.376
POP		0.548	0.568	0.615	0.653	0.152
PUP			0.527	0.383	0.422	0.269
EDU				0.558	0.177	0.218
LIB					0.260	0.103
IND						0.052

Relationships Establishment: MLP networks were used to determine the relationship between waste and the selected generating factors as well as their contribution to the variable Waste. The aim was to analyse how the variables impact waste generation at a communal level across the country. The dataset was divided into three sets: training, testing and validation. A three layer MLP network modelled the relationship between the explanatory variables and waste generation with an $R^2 = 0.819$ and a correlation coefficient equal to 0.915 based on the validation dataset. The architecture of the MLP had five input units using a linear function, twenty hidden units and one output unit, both hidden and output units using logistic functions. Figure 3 shows actual and the network predicted waste generation.

The relative contribution of every variable in predicting waste generation is: 0.413 for POP, 0.169 for LIB, 0.154 for IND, 0.138 for PUP and 0.125 for EDU. All the variables contribute positively to Waste Generation. Figure 4 shows that the higher the level of POP, PUP, IND, EDU or LIB, the higher the level of WG. More importantly, the figure shows the remarkable influence of POP as well as the non-linear relationship between some variables and WG. For example, an increase in POP by 1,000 people will result in an increase in WG between 28.4 and 32.5 tonnes/month. The influence of other variables can be interpreted similarly [28].

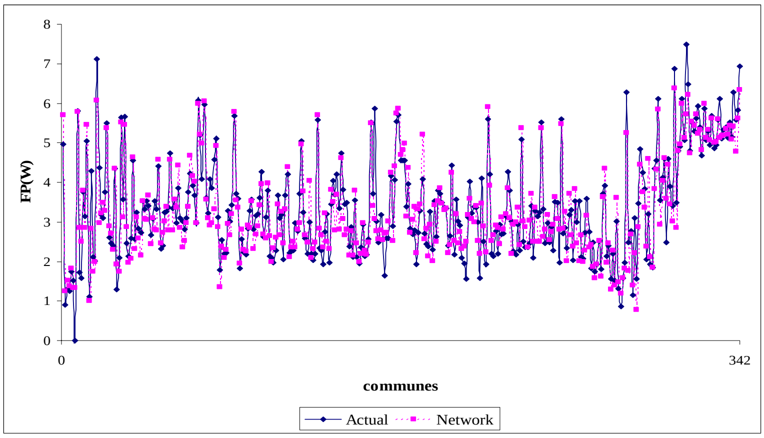

Figure 3: Actual and predicted waste generation for the 342 communes of Chile

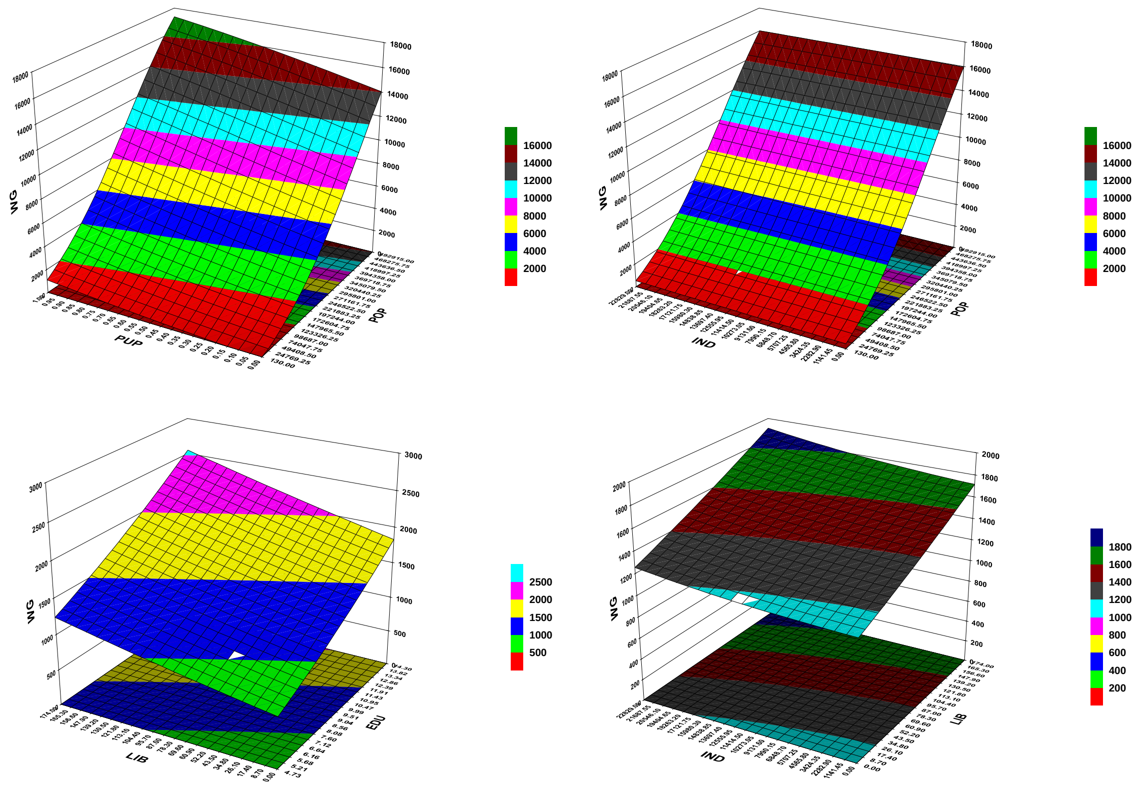

Figure 4: 3D Plots of Waste Generation versus Pairs of Explanatory Variables (POP and PUP, POP and IND, EDU and LIB, LIB and IND)

- ***Stage 2: Clustering of Communes and Selection of Representative Communes***

In this Stage communes are clustered into groups and representatives are selected for forecasting. ***Clustering Communes:*** SOFM were used to cluster the communes into three groups. The net clustered the communes into groups with 91, 156 and 95 communes, based on the significant variables determined in Stage 1. The three groups can be seen in the bi-dimensional plot of the 342 communes shown in Figure 5, where weighted population is plotted against the weighted sum of the other four variables. Weights represent the contribution of variables in the neural network.

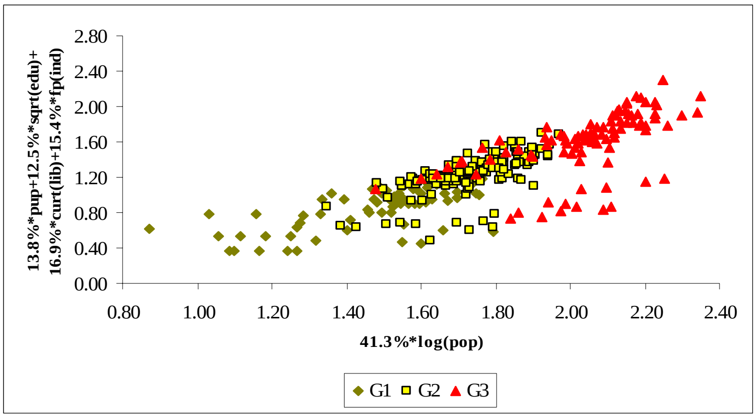

Figure 5: Communes Clustered into Groups

Determining Group Representatives: The most representative communes are those that embody the largest number of communes within a ±15% range of the values of the selected explanatory variables. The representative communes of Group 1 (Marchihue, Cobquecura or Paredones) cover 44% of the communes of the group (40 communes); the representatives of Group 2 (Olmué, Pichilemu or Santa Juana) cover 75% (117) and the representative from Group 3 (Coronel) cover 76.8% of the communes of the group (73 communes), reaching 67.3% of the total number of communes (230 communes).
Data Collection: The selected representative communes were visited to collect data but either they did not have all information or authorities could not be contacted. Therefore, other suitable communes were contacted. In Group 1, data was collected from the Municipality of María Pinto and figures from Pichidegua were collected as a complement [29]. For Group 2, the Municipalities of Peumo and Purén were contacted and their waste generation figures were provided (Data from Peumo [30]). In addition, data from Puerto Aysén and Puerto Natales was collected [29]. For Group 3, data from San Ramón was collected [31,32].

- ***Stage 3: Forecasting Waste Generation***

Data Analysis: The analysis shows that using the communes where data has been readily available, the real coverage range decreased to 39.6% for Group 1 (36 communes), 38.5% for Group 2 (60) and 74.7% for Group 3 (71). This means decreasing the total number of communes covered from 67.3% to 48.8%, i.e., from 230 to 167 communes.
Forecasting Waste Generation: Several MLPs and recurrent networks were trained to forecast waste generation for the three groups, with the aim of forecasting amounts (and trends) in waste generation for the period up to 2010 from past and current data. In modelling terms, this specifically involves forecasting next year generation from previous year explanatory variables. This is a time series (dynamic) analysis and is quite different from the analysis of waste generating factors done as a static case for the whole country in Stage 1. In a time series, next outcome can be highly correlated with the current outcome (e.g. WG next year may be correlated to WG this year). This is possible because this year's outcome may capture substantially the effects of explanatory variables on the next outcome. However, time series models can be further improved if the explanatory variables are also included in order to capture the aspects that are not accounted for by this year's waste alone.
Unfortunately, the data for all the explanatory variables was not available for all the past years due to the lack of data collection in Chile. For example, Groups 1 and 2 only had POP and LIB and Group 3 only POP and PUP. Data for EDU and IND could not be obtained for none of the communes.
Time series were analysed using MLP and recurrent networks. Initially, the networks were trained using only the explanatory variables for which data was available. These used input data for the current year to forecast waste for the next year. Many networks were tested and the best nets were recurrent networks with R^2 values reaching 0.75 for Group 1 (Jordan) and 0.80 for Group 3 (Jordan) both using POP as input but R^2 for Group 2 was only 0.25 with POP and LIB as inputs (Elman). Results showed increases of 14.5% for Group 1 for the period 2001-2010, 13.5% for Group 2 and 5.2% for Group 3 for 2002-2010 period.

Next, in an attempt to improve forecasting accuracy, current per capita waste generation (PCWG) was used as an input along with the current values of the explanatory variables to forecast waste next year. The best selected networks show that PCWG substantially captures the effect of explanatory variables in forecasting WG for the next year. Addition of PCWG increased R^2 for Group 1 from 0.75 to 0.81 (MLP), Group 3 from 0.80 to 0.98 (Jordan). More importantly, R^2 for Group 2 rose from 0.25 to 0.91 (MLP), difference that could be due to inaccuracies in the data for explanatory variables.
Both models, one with and the other without PCWG, showed similar trends and forecasts. However, all the models that incorporated PCWG as input showed a higher forecasting accuracy for the period for which actual data was available for validation. Therefore, these were considered more accurate than those that did not.
Figure 6 shows forecast waste generation and its yearly variation up to 2010 along with the actual waste generation up to 2003. It shows that predictions from the best model for Group 1 are extremely accurate for the period 1998-2003 for which actual data was available for validation. The MLP network forecasts that the waste for the represented commune of Group 1 will reach 100 tonnes/month by 2010. Moreover, it predicts a steady increase in waste generation after 2004, reaching a yearly rate of over 3% by 2007-2008 and then dropping to less than 1% by 2010.

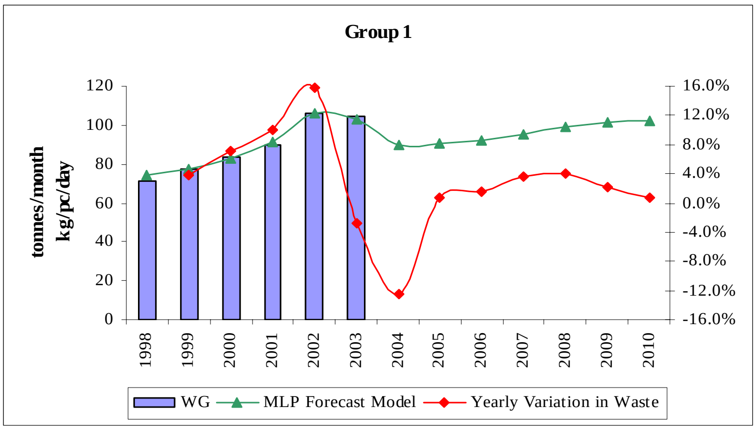

Figure 6: Waste Generation Forecasts up to 2010 for Group 1

Figure 7 shows that the best MLP model predictions for Group 2 for the period 1997-2002 for which actual data was available was extremely accurate. The model forecasts that the level of waste generation will reach around 240 tonnes/month by 2010. There will be a gradual increase in waste generation from 2003 reaching a peak of 3.5% rate of change in 2006 and then dropping to a yearly rate of 0.5% by 2010.

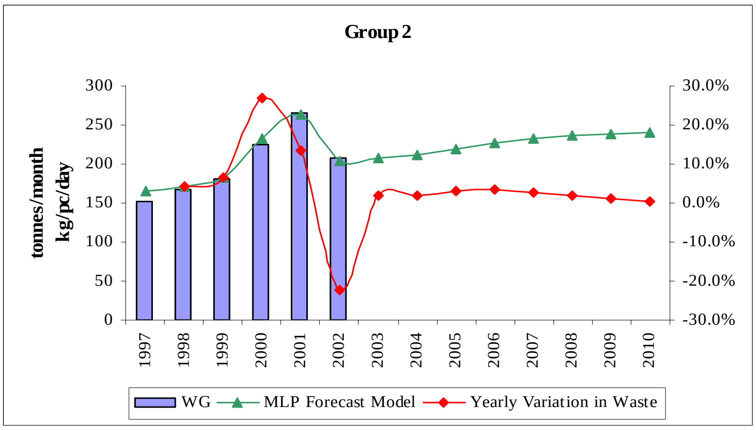

Figure 7: Waste Generation Forecasts up to 2010 for Group 2

Figure 8 shows that the model predictions for Group 3 for the period 1992-2002 are extremely accurate. After 2002, there are fluctuations of WG forecast and the model predicts around 2,900 tonnes/month of waste by 2010. The yearly rate of change of WG peaks at 6% by 2006-2007, reaches 0% by 2007-2008 and then keeps decreasing to –3% yearly rate in 2010. This seems unreal considering the analysed variables and the continued increase in WG through the years. This phenomenon may occur in the commune selected as the representative (San Ramón), which has had a decrease of 0.6% in its population (1992-2002) and not in the Group as a whole (1.3% increase in the same period), a limitation of choosing this commune.

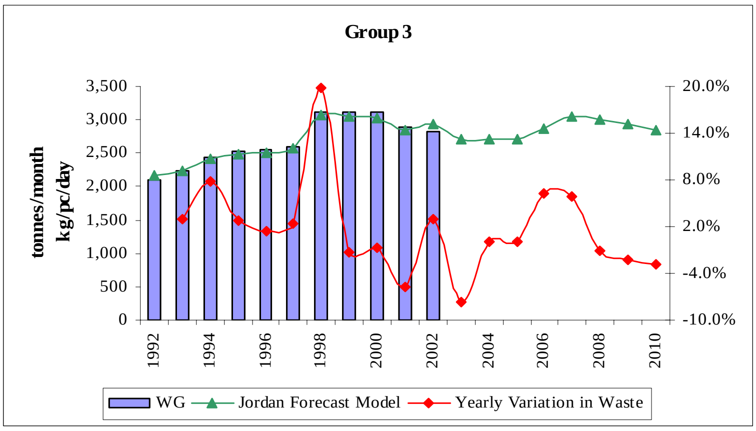

Figure 8: Waste Generation Forecasts up to 2010 for Group 3

Conclusions

This research aims to contribute to the development and improvement of waste management practices in Chile through the design of a communal analysis tool used to study waste generation factors and forecast waste generation. This paper shows the development of a systematic process where factors affecting waste generation in Chile have been determined to ultimately study and forecast waste generation. Groups of communes based on the relevant factors were classified. Representative communes per group were selected and their results were used for estimating future generation for the communes they represent. This research proves the successful application of ANNs in this field, despite the limited data available for the case of Chile.

Through an MLP network ($R^2 = 0.819$) Population was found to be the most important factor contributing to waste generation (41.3%), followed by Number of Libraries (16.9%), Number of Indigents (15.4%), Percentage of Urban Population (13.8%) and Years of Education (12.5%), all contributing positively to waste generation.

With the selected variables, an SOFM clustered the communes into three groups with 91, 156 and 95 communes with clear differences in the values of the independent variables and in the amount of waste generation. The most representative communes were selected from each group. Unfortunately, they could not provide all the relevant data so other communes had to be considered to develop the models. The final selected communes provided just enough data to develop models with a good level of precision, covering 36 communes from Group 1 (40%), 60 from Group 2 (39%) and 71 from Group 3 (75%), i.e., 167 communes (49%).

Data availability was a limitation of this research; however, despite the limited data, the models reached good R^2s and learnt to model the desired output with good accuracy.

When forecasting Waste Generation, recurrent networks with the available explanatory variables produced good results for Group 1 and 3 (R^2: 0.75 and 0.8). The models with and without per capita waste generation (PCWG) produced similar forecasts; however, the models that incorporated PCWG had much higher accuracy for the period for which real data was available for validation and higher overall R^2 values of 0.81, 0.91 and 0.98 for the 3 groups. Therefore, models that used PCWG were considered more reliable.

The best models forecast that the represented communes of Group 1 will reach 100 tonnes/month, Group 2 will reach 240 tonnes/month and Group 3 2,900 tonnes/month by 2010. Yearly waste generation rate for Group 1 peaks at 3-4% by 2008 and drops to less than 1% by 2010, Group 2 rate peaks at 3.5% in 2006 dropping to 0.5% by 2010. Group 3 shows a peak rate of 6% by 2006-2007

dropping to –3% by 2010. However, this phenomenon may occur in the selected commune but not in Group 3 as a whole.
This study demonstrates that despite the limited availability of data, artificial neural networks are capable of forecasting waste generation with good results.

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[i] Governing bodies of communes. There are 342 communes organised into regions.
[ii] Chile is divided into thirteen regions for interior administration and government.