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Operational Predictive Model for a Municipal Waste Incinerator: A Spanish Case Study

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ABSTRACT: This paper describes a study of operational parameters by using the multivariate data analysis and neural networks for a municipal waste incinerator located in Majorca (Spain). The basis of the study also includes the chemometric techniques: linear multivariate regression to develop a model with certain predictive capabilities; linear principal component analysis, which allow the number of variables to be reduced from 17 to 4, thus fostering visualization in a low-dimension space; and linear discriminant analysis to categorize plant data accordingto the month (probability ≈ 70%). Neural network predictive capability was good, with relative errors around 6-8%. These techniques allow all the variables to be analysed simultaneously and focus on the variables which have a significant impact. In this way, the interrelationships between sets of variables, causal relations among input/output variables, seasonal motivated deviations as well as observation variations have been identified.

Key words: Incineration, MWI, Multivariate analysis, Neural networks

INTRODUCTION

Municipal waste management (MWI) covers certain procedures including re-utilization, recycling, landfill disposal, composting, and a variety of combustion processes. Combustion, commonly known as incineration, consists of a controlled oxidation process in which chemical reactions transform carbon species into CO_2. Recently, waste incineration has been a subject of public concern since it leads to the emission of pollutants such as acid gases, particulate matter, nitrogen oxides, heavy metals, and highly toxic trace organic compounds (dioxins and dibenzofurans) to the air, land, and water (Vargas-Vargas *et al.*, 2010). The main advantages of incineration are the reduction of waste (≈ 75% in weight, 90% in volume), the valorization of municipal solid wastes (MSW) by the electric power generated (savings of ≈ 0.05 ton of petrol per ton of MSW) and the almost immediate disposal procedure. Waste management is one of the major problems for modern societies and many works have been published focussing on the analysis of contamination data in water (Christophersen and Hooper 1991; Ennis and Bi 2000; Menció *et al.*, 2008; Ortiz-Estarelles *et al.*, 2001; Ragno *et al.*, 2007; Sarparastzadeh *et al.*, 2007; Subagyono *et al.*, 2005), in sediments (Ausili *et al.*, 1999; Götz *et al.*, 1988; Mildner-Szkudlarz *et al.*, 2008; Nhan *et al.*, 2006; Shine *et al.*, 1995; Sprovieri 2007), in solids (Jalili and Noori 2008; Sadugh *et al.*, 2009), and the effect on human health (Abad *et al.*, 2002; Costabeber *et al.*, 2003; Fabrellas *et al.*, 1999; van Oostdam *et al.*, 2004; Wingfors *et al.*, 2000).

The operation of waste treatment processes is a difficult task due to the great uncertainty in the MSW composition. Further, legal requirements are continually tightening the permitted emissions and it is important to improve predictive control strategies and quick checklists. In this work, an approach to assess the plant operation and management by off-line calculations without disturbing routine operation has been obtained. The main idea is that by applying the multivariate statistical methods and neural networks to the municipal waste incinerator of Son Reus (Majorca, Spain), some predictive guidelines for the operational variables directly related with the

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furnace, the boiler and the turbine, can be provided. Moreover, relationships that are not self-evident (e. g. if several variables are highly correlated, by analyzing some of them, the value for the rest can be inferred) and the way data group in the multivariate space is also investigated in order to asses *normal operation* conditions.

MATERIALS & METHODS

Palma is the major city in Majorca island, which is situated about 350 km from the continent in the Mediterranean sea. In addition to the insularity, Majorca has a high seasonal activity due to tourism, and in certain periods, the MSW go directly to landfill (i. e. over 8 million tourists, most of them during summer). Thus, the waste management is based on the classical 4R's approach (reduce, reuse, recycle and recover). In Spain, MSW produced in 1997-200 was estimated at $1.56 \cdot 10^7$ tons, which means that each inhabitant produces 1.05 kg of waste per day (Abad *et al.,* 2002). In Majorca, the production of MSW is higher than the Spanish average, and it rose from $3.0 \cdot 10^5$ tons in 1990, to $3.5 \cdot 10^5$ tons in 1994, to $4.2 \cdot 10^5$ tons in 1997, which means around 1.5 kg per person per day. It is estimated that around 45% of residues end up in uncontrolled landfills (TIRME 2009). The typical MSW in Majorca composition is: 39.8% organic matter, 19.9% paper, 12.2% plastic, 10.9% glass, 8.1% textiles, 4.3% metals, 4.8% inert matter and 0.08% batteries (TIRME 2009, Greenpeace 1995).

In Spain, $5.42 \cdot 10^5$ tons of MSW were incinerated in 1985 and in 1996 this value was $7.05 \cdot 10^5$ tons (Greenpeace 1995). The total waste treated thermally rose to $1.16 \cdot 10^5$ tons in 1997, which represents around 16.5% of the total Spanish MSW (Abad *et al.,* 2002, Fabrellas *et al.,* 1999). The annual capacity of the MWI plant under study, called Son Reus, represents approximately 58% of the total MSW treated in Majorca and produces around 7% of the electricity consumed in the island. Such a high value is due to the insularity of Majorca. The Son Reus MWI was designed for a waste production of 1.5 kg per day and person, assuming a 5% increase between 1992-2000 and 2% for the following years. The incinerator plant operation started in 1996, with a cost of $9.0 \cdot 10^7$ € (TIRME 2009). The management was carried out by the company TIRME S.A. (Tirme 2009), according to the relevant regulation code (*Real Decreto* 1088/92, Spanish Government and the Guideline 88/369, European Union).

The plant is located 12 km North from the already city of Majorca. There are major tourist resources and industrial areas in the surroundings. The overall aspects of the MWI are shown in Table 1.

The MSW from the waste bunker (A) is introduced into the roller-grate furnace (B). The process is controlled using a distributed control system to ensure some operational parameters (e. g. a minimum of 8% v/v oxygen, a minimum of 850°C and 2 seconds of residence time in the furnace). The MWI has gas-oil auxiliary burners for the start-up and shut-down, which are not used in normal operation. Slag is water-cooled and used as filling material in construction (C), while metals are recycled. The steam boiler (D) has a capacity of 50 tons·h^{-1} per line. The water loop connects the steam boilers with the turbine and alternator (D_1). The surplus of electricity generated (the process consumes 4 MW·h) is distributed through the electricity network (D_2). Water is condensed with an air condenser (D_3) and recycled to the boiler. After that, a semi-dry absorber with lime (E) is used to remove acid gases and heavy metals. Also, active carbon is injected (F) to remove volatile metals (mercury and cadmium) and volatile organic components (phenols, PCDDs, dioxins and furanes). Then, gases go through the bag filters (G) to remove any fly ash. Finally, gases are released from the stack (H). A small percentage of the ash (I) is reintroduced into the scrubbing system to improve its performance, while its final disposal is stabilization/solidification with cement. The layout of the plant presents two identical incineration units and a unique gas-cleaning system (Fig. 1).

Table 1. Technical profile of the Son Reus MWI (per incineration unit)

Incineration units	2
Thermal capacity/MW	45.15
Capacity/tons·day^{-1}	18.75
Calorific power of MSW/ kcal·kg^{-1}	1530-2070
Combustion air/Nm³·h^{-1}	77.57
Maximum steam production/kg·h^{-1}	50200
Steam pressure/bar	40
Steam temperature/°C	400
Boiler output gas temperature/°C	180-200
Maximum power/MW·h	42.6
Gas flow/Nm^3·h^{-1}	100000
Production of ashes/tons·day^{-1}	0.30
Production of slag/tons·day^{-1}	4.0

The public taxes are calculated according to the MSW, the operating costs, the electric power generated as well as the pay-off of the MWI. Due to the MSW heterogeneity, it is almost impossible to analytically and quantitatively characterize their composition and therefore the energy produced in the MWI has a high uncertainty. The key aspect is the accurate prediction of the calorific power (CP, computed at 1 atm and 25°C) from the MSW, as it is the variable used to describe the raw material. At the moment, these calculations are performed from the mass and energy balance. In this general framework the influence of each variable and their complex interactions can not be properly fixed.

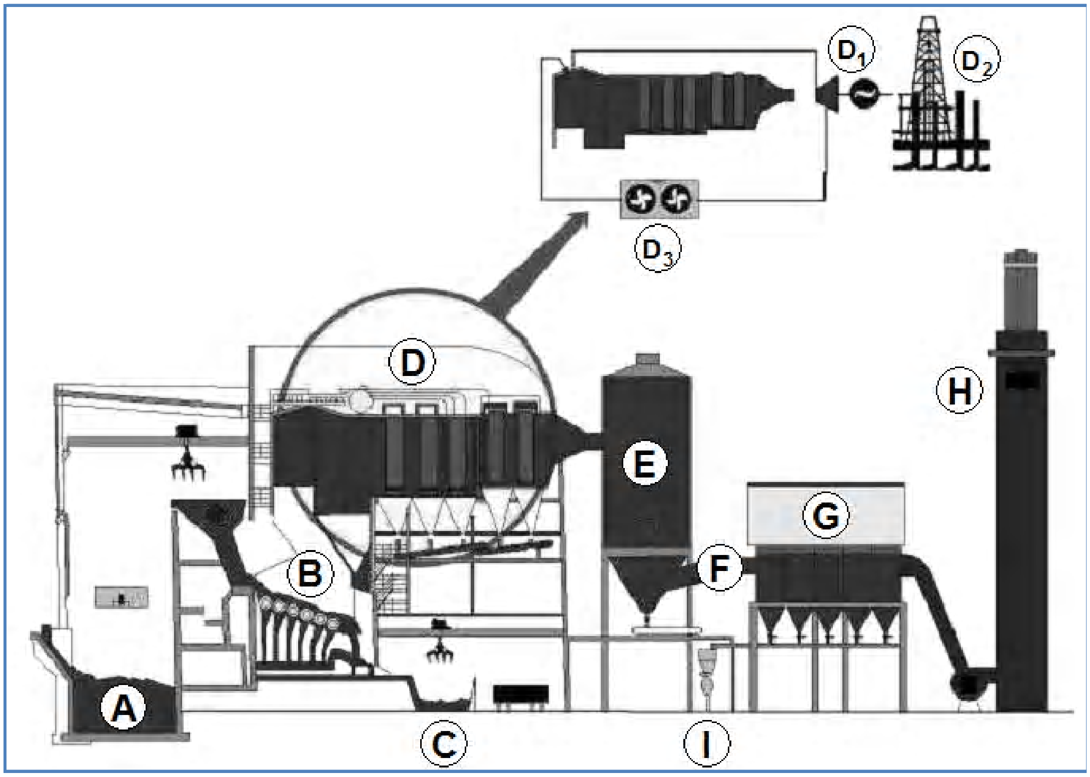

Fig. 1. Schematic representation of the Son Reus MWI: A: bunker waste; B: furnace; C: slag; D: boiler, D_1: turbine, D_2: alternator, D_3: electricity network, and D_4: air condenser; E: semi-dry absorber; F: activated carbon injection; G: bag filter; H: stack; and I: fly ash

An emission and inmision plan has been done and all parameters are clearly below legal limits (Real Decreto 1088/92 from the Spanish Government and guideline 88/369 from the European Union).

The purpose of this paper is to survey the basic principles and methods of multivariate data analysis for plant data (Brereton 1999, Gnanadesikan 1977, Manly 2004, Morrison 2002). The main strength of multivariate analysis is the discovery of the correlation structure of the data that is not self-evident in the multivariable space (e. g. due to redundant information). Also, it is of considerable aid in detecting similarities, differences, and relationships among the variables (Boente G. and Fraiman 2000, Mertler and Vannatta 2004, Montgomery 1998, Rene and Saidutta 2008, Ross 1999). Whether these variables should be measured in the plant for security/legal considerations is not considered in this work. As multivariate analysis becomes more common, the dangers of its misuse also increase (Ocaña *et al.*, 1999, Parinet *et al.*, 2004, Sparks *et al.*, 1999, Zitko 1994). In this case, the analyses were performed using SPSS™ (SPSS 2007).

There are no strict rules about how to pre-process a data set before multivariate projection analysis. Usually, to eliminate the effect of widely different levels among the variables (e.g. different units) are centered by subtracting the mean and rescaled by dividing by its standard deviation. These normalization procedures give equal weight to each variable and avoid dominating the analysis with variables with large variances.

The objective of linear multivariate regression (LMR) is to establish the relationship between the variables and obtain a model with predictive capabilities to estimate the CP. The step-wise procedure with the Pearson coefficient to assess the significance of each input variable was used (Equation i).

$$y = a + b \cdot x_1 + c \cdot x_2 + d \cdot x_3 + \cdots + n \cdot x_n \qquad (1)$$

To look at a cloud of points in a multivariate space, one would like a procedure that produces orthogonal axes, preserves relative distances and reduces the number of dimensions. Linear principal component analysis (LPCA) has all these characteristics. A linear principal component (LPC) is a linear combination of the original variables and explains most of the variance with a reduced number of variables. Moreover, they offer visualising patterns and variable relationships in easily interpretable graphical plots. The percentage of the total variance that each LPC collects varies widely, and typically just a few ones explain the highest part of the variance observed in the data.

Cluster analysis (CA) was performed to find the variable grouping. In this technique groups are defined directly by the data. Linear discriminant analysis (LDA) is a technique used to capture associations among several series of data and develop rules for classifying data into groups. Grouping criteria are defined *a priori*, and step-wise LDA computes which variables are significant to explain the differentiation. To do that, LDA derives variables (called discriminant functions) that are combinations of the original variables, which discriminate maximally between the groups.

The Neural Networks (NN) technique, a completely different technique, was used to process the data. The NN has found solid applications during the last decade and it is developing rapidly. Based on an idealized model of the biological neuron, the calculation paradigm of NN is able to represent information for complex systems. In the NN model, the input signal (external or from other units of the network) is given to a unit (neuron) that processes it and sends an output to other units or to the network output. In the generic case, all pairs of neurons are connected, and the network performance is strongly dependent on the weighting structure. The main benefits of the NN approach (Bishop 1996, Hagan *et al.*, 2002, Haykin 1994, Ripley 1996, Thangavel and Kathirvalavakumar 2002, Yu *et al.*, 2002) consists in its remarkable ability to learn and generalize patterns and their robust behavior in the presence of noise. As a consequence, the NN approach is successfully used for modeling systems in which detailed governing rules are unknown or difficult to formalize, but the input-output set of variables is known (Eyupoglu *et al.*, 2010, Rene and Saidutta 2008). NN also offer incentives for cases when input-output data are noisy and when high processing speed is required (Jalili and Noori 2008). Calculations were performed using MATLAB® (MatLab 2009) capabilities and the neural networks toolbox.

RESULTS & DISCUSSION

The plant data were retrieved from the on-line monitoring system (1999-2001) and corresponds to the daily averages of the Son Reus MWI (line 1). Several variables from the furnace were measured: flowrate and temperature of the combustion gases (CGF and CGT); flowrate and temperature of the primary air (PAF and PAT); flowrate and temperature of the secondary air injection (SAF and SAT); gas-oil flowrate (GOF) used in the auxiliary burners; and the reference oxygen content (OCR), measured in the furnace effluent. The water flowrate, temperature and pressure (WF, WT, and WP) were measured in the boiler. The turbine variables were also included: the vapor flowrate temperature and pressure (VF, VT, and VP). In addition, the lower calorific power of the MSW (CP) was incorporated to check for the relationship among the variables. According to the advise of the plant personnel, the ambient temperature (T) was also considered. Thus a matrix of 17 variables × 907 days of routinely analyzed parameters was used in this work. Only a few representative results of the numerous calculations are presented in this paper (Figs 2 to 5 and Tables 2 to 5).

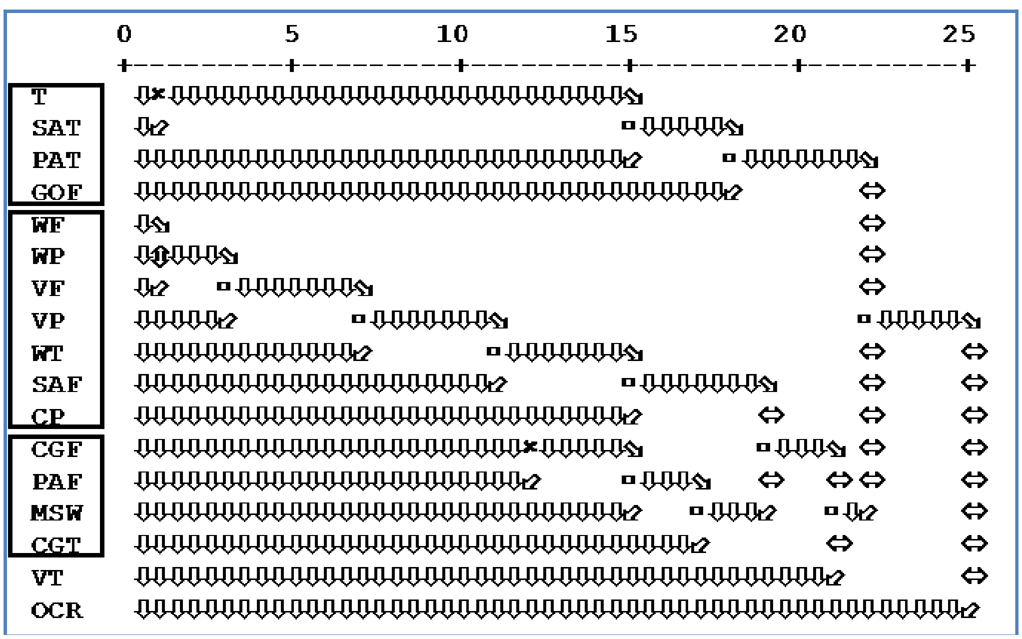

Fig. 2. Cluster analysis for the variables considering all data

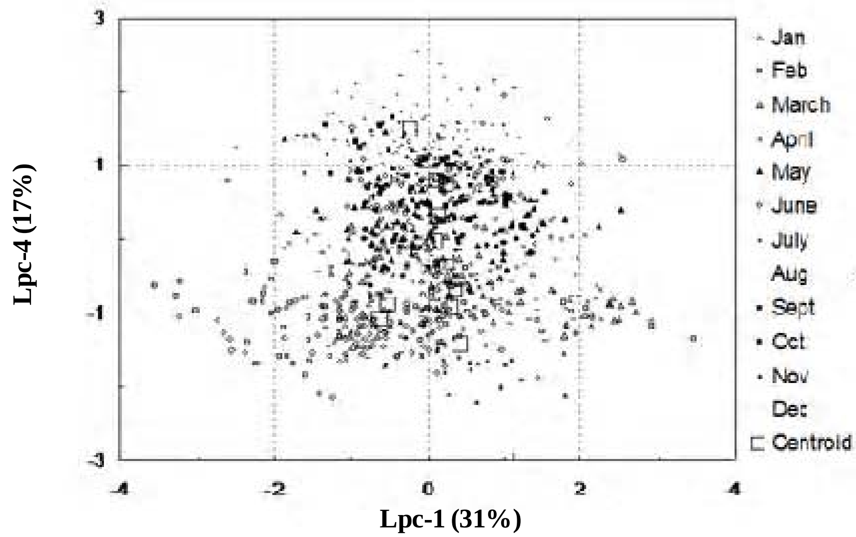

Fig. 3. LPCA based on the correlation matrix. (a) LPC-1 vs LPC-2

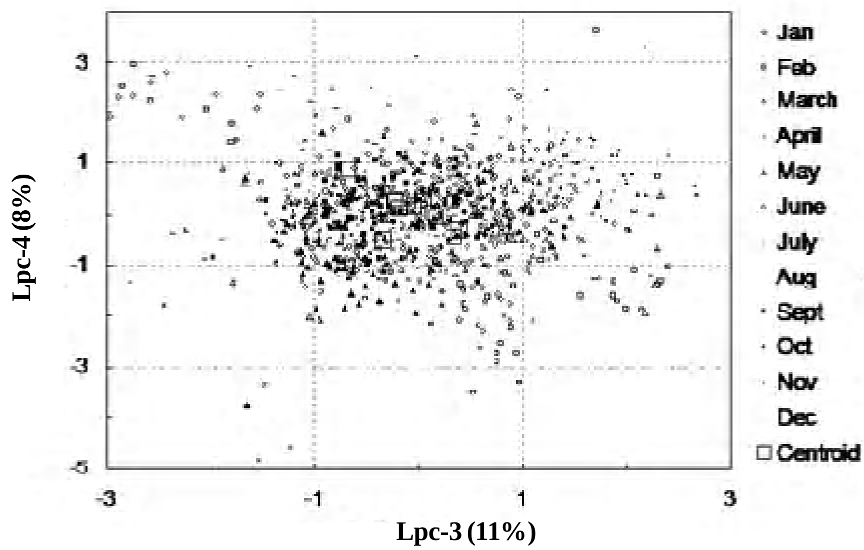

Fig. 4. LPCA based on the correlation matrix. (b) LPC-3 vs LPC-4

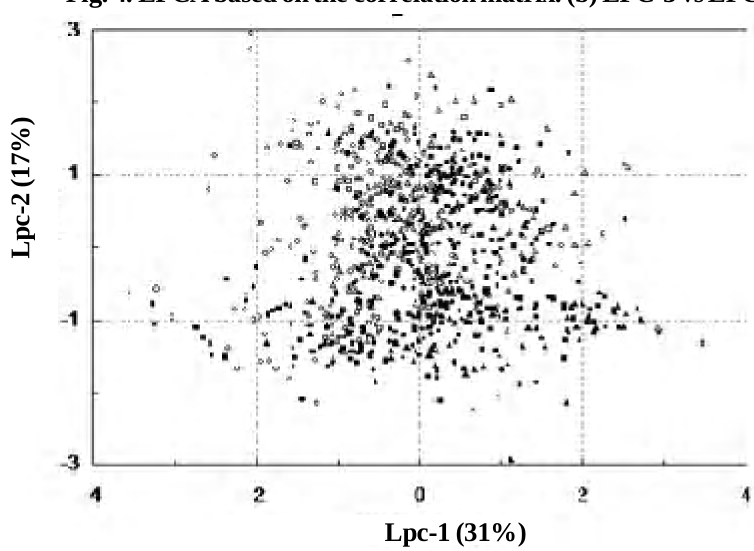

Fig. 5. PCs score plot in the space defined by: (a) LPC-1 vs LPC-2. CP parameterization: ○ = 1.5<CP<1.72☐ = 1.72<CP<1.77; Δ = 1.77<CP<1.82; • = 1.82<CP<1.87; ■ = 1.87<CP<1.95; ▲ = 1.95<CP<2.14; T = group centroid

Table 2. Descriptive statistics of the original data set (907 data)

	Mean*	Median	Standard deviation	Minimum	Maximum
CGF/Nm^3/h	8.23±0.024	8.20	0.37	6.93	9.53
CGT/ ^{o}C	231±0.67	231	10	185	253
GOF/L/h	8.71±1.2	1.20	18	0.500	188
CP/cal/g	1.82±0.0058	1.82	0.090	1.53	2.14
MSW/ton/h	469±1.3	470	20	379	571
OCR/% v/v	8.02±0.053	7.90	0.82	5.70	17.2
PAF/Nm^3/h	5.30±0.13	5.31	0.20	4.42	5.86
PAT/^{o}C	145±0.80	147	12	88.9	180
SAF/Nm^3/h	1.18±0.011	1.19	0.17	0.640	1.63
SAT/ ^{o}C	31.3±0.34	31.2	5.3	14.7	41.8
T/^{o}C	20.2±0.40	20.1	6.1	6.70	33
VF/ton/h	45.5±0.13	45.5	2.0	38.5	52.6
VP/bar	41.6±0.020	41.6	0.31	40.6	42.5
VT/^{o}C	398±0.28	400	4.2	355	404
WF/ton/h	47.6±0.13	47.4	2.0	40.6	54.3
WP/bar	51.8±0.056	51.8	0.87	48.9	54.7
WT/^{o}C	127±0.15	127	2.3	115	137

* Significance level = 95%

Table 3. Results of the LPCA: eigenvalues and variance explained by each LPC

LPC	Eigenvalues	% of variance
1	5.28	31.1
2	2.85	16.7
3	1.94	11.4
4	1.32	7.76
5	1.23	7.26

Table 4. Matrix of the linear principal components

	LPC-1	LPC-2	LPC-3	LPC-4	LPC-5
WP	**.979**	$5.49\cdot10^{-2}$	$1.66\cdot10^{-2}$	$5.00\cdot10^{-2}$	$-7.60\cdot10^{-2}$
WF	**.936**	$-7.92\cdot10^{-2}$	.108	$-5.33\cdot10^{-2}$	$-7.23\cdot10^{-2}$
VF	**.930**	-.161	.123	$-1.32\cdot10^{-2}$	-.148
VP	**.881**	.196	$7.54\cdot10^{-2}$	$8.48\cdot10^{-2}$	$-9.19\cdot10^{-2}$
WT	**.740**	.457	-.158	.143	$3.14\cdot10^{-2}$
T	.113	**.918**	$-9.83\cdot10^{-2}$	$2.13\cdot10^{-2}$	-.113
SAT	.108	**.904**	-.152	$-6.00\cdot10^{-2}$	-.135
PAT	$4.31\cdot10^{-2}$	**.537**	.238	-.220	$6.91\cdot10^{-6}$
PAF	.313	**.441**	.347	-.301	.391
GOF	-.188	**.414**	.154	$6.77\cdot10^{-2}$	.181
CGT	-.139	$-2.71\cdot10^{-2}$	**.880**	$5.34\cdot10^{-2}$	-.132
CGF	.388	$7.67\cdot10^{-2}$	**.751**	$-9.44\cdot10^{-2}$	$-1.34\cdot10^{-2}$
MSW	.303	$5.78\cdot10^{-2}$	.264	**-.823**	$5.25\cdot10^{-4}$
CP	.398	-.371	$6.15\cdot10^{-2}$	**.745**	-.155
VT	.159	$8.49\cdot10^{-2}$	.125	**.544**	.228
OCR	-.102	$-9.90\cdot10^{-2}$	$-4.95\cdot10^{-2}$	$5.46\cdot10^{-2}$	**.818**
SAF	.499	$-7.78\cdot10^{-2}$	.281	-.132	**-.645**

Table 5. LDA showing monthly allocation of individual data. Numbers refer to the month (1= January; ...; 12= December)

Original month	Predicted month 1	2	3	4	5	6	7	8	9	10	11	12	Total number
1	67	16	3	1							1	5	93
2	25	39	13	3								4	84
3		8	50	18	2				1	3		5	87
4			23	46	11	1				5			86
5			1	9	59	8			5	5			87
6				1	8	54	18	2	5	2			90
7				1	3	9	47	17	14				91
8							10	77	5				92
9					1	2	4	3	42	5			57
10			1	2	2				6	34	2		47
11										1	32	6	39
12	1	3	3								3	44	54
% correct	72	46	57	53	68	60	51	84	77	72	82	81	

Error and Detection of Outliers

The classical statistical analyses were investigated (histograms, confidence analysis) and the general characteristics of each variable are shown in Table 2. Typical exponential profiles were detected for variables adjusted to the legal limit (e. g. GOF, VT) while other variables behave as normal distributions (e. g. SAF, CP). Variables such as SAT and T show a peculiar profile that clearly indicates the presence of outliers. The outliers detected were not considered to avoid the influence of operational parameter that are far from the normal operating conditions. The noise rejection capacity of the neural networks revealed that a few data are affected by errors of measurement, due to significant relative errors. Moreover, we checked with the operational planning and the documentation of incidences and all these data coincide with operational upsets or shut-down/start-up periods.

This section was carried out to have a straightforward model with predictive capabilities for the CP (variable used to characterize the MSW) and as a tool to compare the behavior of the two incineration lines installed in the MWI.

Two different models were used, both of them consider a step-wise inclusion of variables; that is, a variable is discarded if its contribution is not significant or alternatively if the variability is represented by a variable that has already been included within the model. If all variables are considered (r^2=0.934) the variables are selected in the following order: MSW, VF, CGT, VP, PAT, GOF, VT, SAF, PAF, SAT, T and WT. If just input variables to the MWI are considered, the model also exhibits certain predictive capabilities (r^2=0.836). As expected, the order in which the variables are included change (MSW, GOF, WT, PAT, SAF, SAT, WP, PAF, WF and T). The coefficients of the model are shown in Equation ii, thus emulating a feed-forward control strategy. The sign of most coefficients could be predicted *a priori* (e. g. GOF should be negative), while for others (e. g. MSW) no justification was found.

$$\begin{aligned} CP = {} & 2.53 - 3.00{\cdot}10^{-3}MSW - \\ & 4.38{\cdot}10^{-4}GOF - 1.23{\cdot}10^{-3}WT - \\ & 1.96{\cdot}10^{-3}PAT + 1.28{\cdot}10^{-3}SAF - \\ & 7.96{\cdot}10^{-3}SAT + 1.51{\cdot}10^{-3}WP + \\ & 4.86{\cdot}10^{-4}PAF + 2.20{\cdot}10^{-3}WF + 4.05{\cdot}10^{-3}T \end{aligned} \qquad (2)$$

As can be seen (Fig. 2), the variables group each other in several well-defined clusters (the distance in the horizontal axis is a measure of group closeness). These groups are: mass and energy balance in the boiler (WF, WP, VF, VP, WT, SAF and CP); temperatures (T, SAT, PAT) and GOF; and stoichiometric aspects of the whole plant (CGF, PAF, MSW and CGT). VT and OCR seem to behave independently of any other variable.

The correlation matrix shows an average dependence among variables, pointing out that the set of data is not highly redundant. The Kaise-Meyer-Olkin (KMO) and Bartlett spherical tests (Everitt and Dunn 1992) were performed to know if the use of multivariate techniques is suitable *a priori*. In this case, although the results from the first method neither recommend nor avoid LPCA (KMO=0.647), the second one exhibits a non-identity correlation matrix, and thereby LPCA is a promising technique.

From the initial 17 variables, LPCA derives just 5 factors, which makes easier the analysis and interpretation of results. These factors (Table 3) represent 74.3% of the information contained in the original data.

The communality values show how much variance of a single variable is condensed in all four factors. In this case VT, PAF and GOF were the worst represented variables (<40%). The communalities captured by the LPCs for any other variable ranges from 66% (PAF) to 93%(VF).

To provide an interpretable factor matrix for the LPCA, the covariance matrix was rotated using the varimax method (SPSS 2007). The objective was to achieve a matrix where each factor has a high correlation with just a few original variables, while all the other factors should have values close to zero. Results are shown in Table 4, where a certain grouping of variables was observed. As expected, a certain similitude with results from the CA is also found. The first LPC, explains the greatest part of variation in the data (31%), and includes almost all variables related with the boiler except vapor temperature, thus stating that these are the variables with higher correlation. High values of the LPC-1 mean that all the variables have high values, as all the correlation values are positive. This result has a clear explanation, as it states that among all the variables considered the ones related with a *classical* unit operation (i. e. reboiler) are most correlated, because the mass and energy balance can be rigorously performed (i. e. the vapor produced depends on the water input). The second LPC represents 17% of the total variance and is dominated by T, SAT, PAT PAF and GOF. This factor includes the energy inputs to the furnace, and all variables are physically related to the combustion. It is important to highlight that PAF in spite of being included in this factor has a considerable contribution in all LPCs, and therefore is correlated with a great number of variables. The third LPC covers 11,4% of the total variance. CGT and CGF rule LPC-3. The great variability in the MSW masks the relationship established by the mass and energy balance, and these two variables seem to behave independently of the other parameters, as shown by the covariance matrix. The last two LPCs include each one around 7% of the total variance. The fourth one contains MSW, CP and VT while the fifth OCR and SAF. It is not surprising that no physical meaning was found for these factors, as subsequent LPCs explain successively smaller variance of the information contained in the original variables. The behavior of SAF is very similar to that of PAF, since the correlation coefficients with LPC-1 is also high. High values of CP imply low values of MSW, thus stating a reverse relationship between variables These results agree with those obtained from the CA (grouping of variables) and the LMR (relationship between variables).

Next, the most evident representations are shown. One of the aspects that was checked was the seasonal variation of all variables, and its effect on the MWI operation. Fig. 3 confirms the role of LPC-1 and LPC-2 in the data distribution. This phenomenon was also confirmed with the parameterized plot of the LPCs. For example, LPC-2 contains the original variable CP: low values of LPC-2 (winter) correspond to high values of CP, while in summertime the opposite behavior is found, due to the variability in the MSW composition (higher organic fraction). Fig. 4 also shows the seasonal variation, probably due to the effect of MSW.

A result that may have more importance is how the process variables behave depending on the time of the year the plant is operating and in particular what is the behavior of some key variables (e. g. CP). The previous knowledge of the process makes easier the analysis, as the possibilities are combinatorial (i. e. OCR and T should not be considered). In this case, a clear graduation from bottom-right to the top-left part depending on the CP was detected (Fig. 5). If LPC-3 and LPC-4 are considered, a clear differentiation from bottom to top is found, probably because CP is included in these components. (Fig. 6).

The LDA is performed after the LPCA and it has proven to be a very useful technique to verify the pattern in which data are grouped. The significance values, obtained by means of analysis of variance (ANOVA) are not very close to zero, expressing *a priori* that the LDA model will have a medium-high classification performance. The result of the LDA is that the model classifies correctly 65.0% of the original data according to the month, and where WT, GOF and OCR were not considered. Results are reported in Table 5, where actual and predicted group membership are shown. Because the months are in effect a continuum that is artificially separated, we should not be surprised that a better discrimination is not achieved. It should be remembered that if allocation were completely random we would only expect a 8.3% correct allocation. Due to the characteristics of the Mediterranean climate, some spring/autumn data are missclasified. Also, the lower number of data corresponding to October, November and December is due to plant shut-downs.

According to the classification for the CP divided into six intervals (see Figs 5 and 6), the model is able to classify 80.5% of the cases correctly using all variables. With an step-wise analysis this value is almost the same (79.7%), just considering 9 variables (VF, VT, VP, WF, CGT, PAT, SAT, GOF, MSW) thus indicating that turbine and furnace variables dominate the analysis. If just the input variables are considered, the classification performance drops to 60.5% where all variables are considered (WF, WP, WT, PAF, PAT, T, SAF, SAT, GOF, MSW). The order in which the variables are introduced into the model also adds some information (e. g. GOF was among the last variables, as it is used when MSW have a

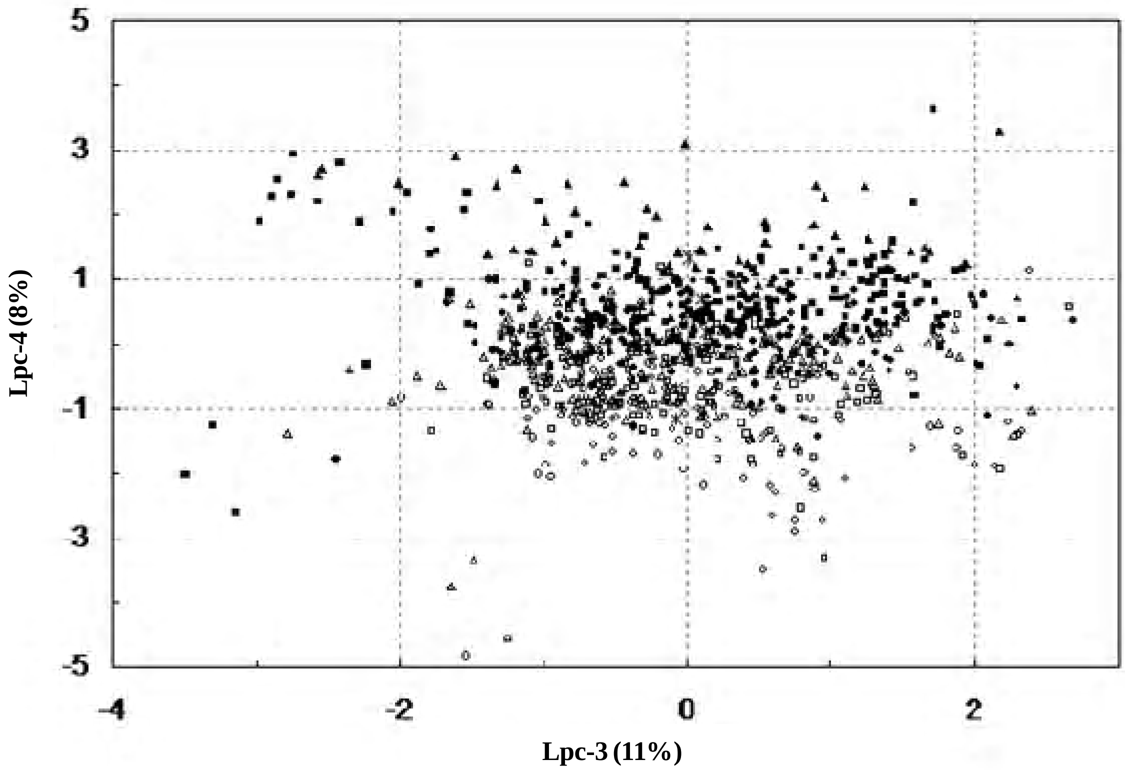

Fig. 6. PCs score plot in the space defined by: (b) LPC-3 vc LPC-4. CP parameterization: ○ = 1.5<CP<1.72 □= 1.72<CP<1.77; Δ = 1.77<CP<1.82; • = 1.82<CP<1.87; ■= 1.87<CP<1.95;▲= 1.95<CP<2.14; T = group centroid

Table 5. LDA showing monthly allocation of individual data. Numbers refer to the month (1= January; ...; 12= December)

Original month	Predicted month												Total number
	1	2	3	4	5	6	7	8	9	10	11	12	
1	67	16	3	1							1	5	93
2	25	39	13	3								4	84
3		8	50	18	2				1	3		5	87
4			23	46	11	1				5			86
5			1	9	59	8			5	5			87
6				1	8	54	18	2	5	2			90
7				1	3	9	47	17	14				91
8							10	77	5				92
9					1	2	4	3	42	5			57
10			1	2	2				6	34	2		47
11										1	32	6	39
12	1	3	3								3	44	54
% correct	72	46	57	53	68	60	51	84	77	72	82	81	

very high humidity or for plant start-up and shut-down). In all the analysis performed, the model prediction is better for the extreme intervals (≈70-80%) than for intermediate intervals of CP (≈15-20%).

The NN approach has been used to investigate the prediction ability to infer the CP from the data set. The original data was divided into two subsets: 90% of the data were used to train the network and the rest were used to test the ability of the model. A multilayer feed-forward NN architecture with the backpropagation training algorithm was used to compute the network biases and weights (Hagan *et al.*, 2002). Two layers of neurons were considered (20 neurons in the input layer and one neuron in the output layer), with the tan-sigmoid transfer function for the hidden layer and the purelin transfer function for the output layer. The quasi-Newton Levenberg-Marquardt algorithm was used to train the NN and the early stopping method (based on the gradient of the mean square error) was applied to prevent any overfitting.

The first study was carried out considering the entire set of the variables as inputs to the NN and the CP as output variable (case I). The results illustrate a very good prediction characteristic of the NN prefigured by the straightforward learning aptitude (r^2=0.995 for the training set of data). At the same time, the generalization capability of the trained NN, performed on the test set of data, proved to be very good. (r^2=0.975).

As a result of the multivariate analysis, an additional exploration of the data was performed just considering the input variables (MSW, GOF, WT, PAT, SAF, SAT, PAF, WF, WP and T). In order to test the robustness of the NN, two different approaches had been considered. The first approach was to select homogeneously distributed test data (case II), while the second was to use test data corresponding to the last time period of the set (case III). In both cases, the NN exhibits a good fit between the original and the NN output data for the training subset (r^2 > 0.995). The same favorable fit was also preserved for the test data set demonstrating a good generalization property of the NN. Results for case II and case III are shown in Figs 7 and 8, respectively. In both cases, relative errors lower than 6% and 8% are found.

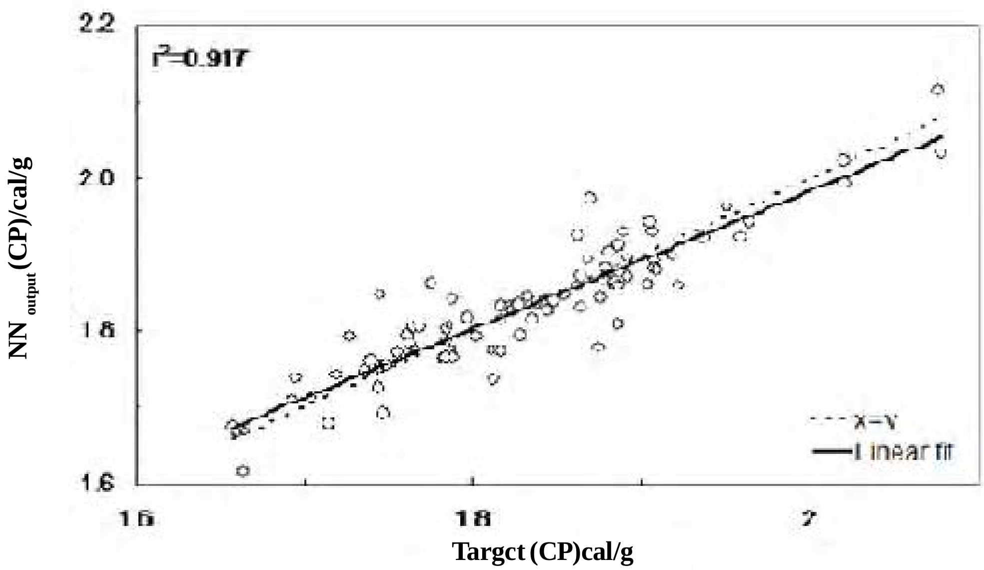

Fig. 7. NN prediction ability for the CP. (a) Case II

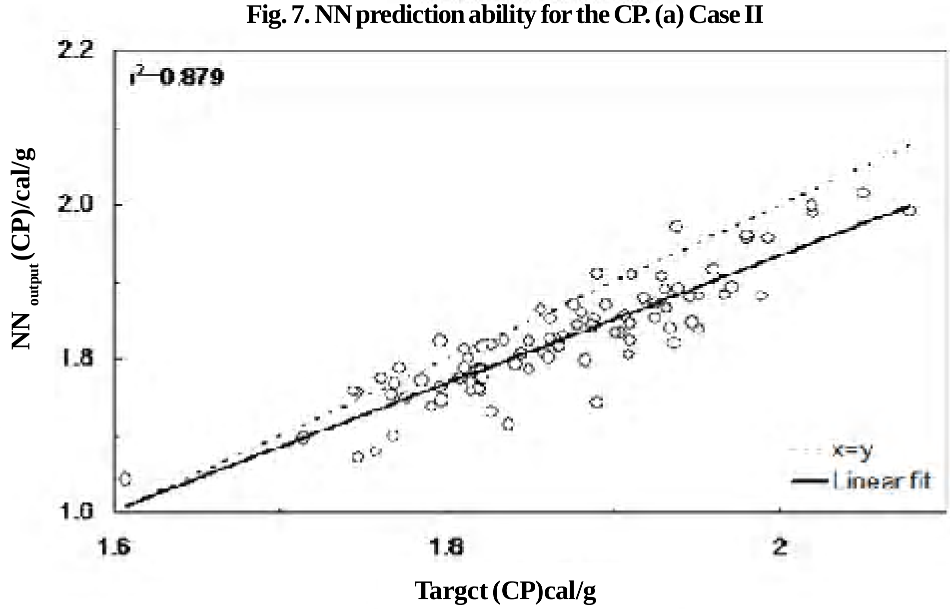

Fig. 8. NN prediction ability for the CP. (b) Case III

CONCLUSION

Multivariate methods provide a large arsenal of suitable techniques, whose potential has not yet been exploited to the full. The above example demonstrates that multivariate techniques can provide a deeper insight into the internal structure of the data and help to reach conclusions that are not immediately obvious.

Both the LMR and the NN models predict the CP from the MWI input variables with an acceptable relative error. This capability is a potential source of improvement for monitoring and operating the MWI and was found to be very useful for comparing both incinerator lines. Also, the use of LPCA allows a reduction of the number of variables from 17 to 5 maintaining 75% of the variance contained in the original data. The LDA model exhibits very good predictive capabilities (65% for the month and 80% for CP). The NN approach may be extended to dynamic data and it may help to detect upsets in feed properties and perform efficient real time control.

NOMENCLATURE

ANOVA	Analysis of variance
CA	cluster analysis
CGF	flowrate of the combustion gases/ $Nm^3 \cdot h^{-1}$
CGT	temperature of the combustion gases/ ^oC
CP	calorific power of the MSW/$cal \cdot g^{-1}$
GOF	gas-oil flowrate/$L \cdot h^{-1}$
KMO	Kaise-Meyer-Olkin
LDA	linear discriminant analysis
LMR	linear multivariate regression
LPC	linear principal component
LPCA	linear principal component analysis
MSW	municipal solid waste/$ton \cdot h^{-1}$
MWI	municipal waste incinerator
NN	neural networks
OCR	reference oxygen content/% v/v
PAF	flowrate of the primary air/$Nm^3 \cdot h^{-1}$
PAT	temperature of the primary air/^oC
SAF	flowrate of the secondary air/$Nm^3 \cdot h^{-1}$
SAT	temperature of the secondary air/^oC
T	ambient temperature/^oC
VF	vapor flowrate/$ton \cdot h^{-1}$
VP	vapor pressure/bar
VT	vapor temperature/^oC
WF	water flowrate/$ton \cdot h^{-1}$
WP	water pressure/bar
WT	water temperature/^oC

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