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Research article

Forecasting municipal solid waste generation using prognostic tools and regression analysis

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A B S T R A C T

For an adequate planning of waste management systems the accurate forecast of waste generation is an essential step, since various factors can affect waste trends. The application of predictive and prognosis models are useful tools, as reliable support for decision making processes. In this paper some indicators such as: number of residents, population age, urban life expectancy, total municipal solid waste were used as input variables in prognostic models in order to predict the amount of solid waste fractions. We applied Waste Prognostic Tool, regression analysis and time series analysis to forecast municipal solid waste generation and composition by considering the Iasi Romania case study. Regression equations were determined for six solid waste fractions (paper, plastic, metal, glass, biodegradable and other waste). Accuracy Measures were calculated and the results showed that S-curve trend model is the most suitable for municipal solid waste (MSW) prediction.

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1. Introduction

Human activities always produce waste, and the generation rates increase with population expansion and economic growth (EEA, 2003; Giusti, 2009). They say that the waste amount could reflect the socio-economic development, industrialization and urbanization (Hogland and Marques, 2007; Pires et al., 2011). In fact, waste generation is a symptom of raw material and energy losses, thus leading to additional costs to society for collection, treatment and disposal (EEA, 2003; Schiopu et al., 2007).

Waste management is becoming an emerging problem for national and local governments, since the manners in which the growing amount of solid waste are managed do influence the human health and the environment and could contribute significantly to resources conservations (Berechet and Fischer, 2015; Costiuc et al., 2015; Ghinea et al., 2012; Giusti, 2009; Ngoc and Schnitzer, 2009). Environmental pressures from generation, collection and processing of waste including emissions to air, soil and water have different impacts on the human health and the environment (Bjelić et al., 2015; Luca and Ioan, 2014; Orlescu and Costescu, 2013; Schiopu et al., 2009; Taboada-González et al., 2011). Effective management of solid waste has become environmentally, economically and socially mandatory due to the escalation of

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environmental problems emerging from solid waste generation (Panaitescu and Bucuroiu, 2014). According to the European Landfill Directive, waste management hierarchy recommends the decrease of waste quantity landfilled and the increasing in weight and preference for waste minimization, recycling and reuse alternatives (Costuleanu et al., 2015; Gaba et al., 2014; Ghinea et al., 2014; Panaitescu and Bucuroiu, 2014).

Modeling approaches and structures are becoming increasingly applied to ensure a further accurately representation of the tangible municipal solid waste (MSW) management systems, especially in situations where lots of waste streams should be coped, from different sources and at various time phases, involving dozens of possible processes devoted to collection and treatment (Ghinea and Gavrilescu, 2010a; Levis et al., 2013). In general, planning and properly operation of solid waste management systems are affected by the evaluation of MSW streams and by more precise predictions of the waste amounts possible to be generated (Abbasi et al., 2013; Ghinea, 2012; Pires et al., 2011; Wang et al., 2012).

Since the prognosis of solid waste quantities represents an increasingly challenge for policy makers and planning, various predictive and prognosis models were proposed and developed in order to ensure sustainable planning, management and valorization of MSW.

Artificial Neural Networks (ANN) were applied as a reliable modeling tool by for the prediction of waste generation during different seasons, over short, medium or long time stages, based on absolute relative error and correlation coefficients (Zade and Noori, 2008). Four statistical indexes were used by Shamshiry et al. (2014): Mean Absolute Error (MAE), Mean Absolute Relative Error (MARE), Root Mean Square Error (RMSE), and correlation coefficient (R^2) for selection of the best forecasting waste generation model, using for prediction 10–20 neurons in the hidden layer for network training with 4 variables. ANN was applied for waste prediction in Serbia considering 4 inputs (economic indicator, average age of population, level of education and municipal sector), 10 neurons in hidden layer and 6 outputs (organic waste, paper, glass, metal, plastic and other waste) (Batinic et al. (2011). Karaca and Özkaya (2006) proposed a method based on the so called backpropagation algorithm (*n*eural *n*etwork-based *lea*chate *p*rediction method; NN-LEAP) for modeling leachate flow-rate in a municipal solid waste (MSW) landfill. ANN was also combined with Multiple Linear Regression for seasonal municipal solid waste generation prediction for 20 cities from Iran (Azadi and Karimi-Jashni, 2015). The results showed that Multiple Linear Regression has poor prediction performance, while ANN has a higher predictive accuracy.

Various regression analyses were performed in order to estimate how different variables can affect waste generation on long-term, considering urban population, gross domestic product, consumption level of residents as main factors which influences waste production (Grazhdani, 2015; Wei et al., 2013). Autoregressive Integrated Moving Average (ARIMA) time series model was applied by Owusu-Sekyere et al. (2013) to analyse the dynamics of solid waste generation using ARIMA (1, 1, 2); ARIMA (2, 1, 1) and ARIMA (1, 1, 1) models. Apart from these ARIMA models, Mwenda et al. (2014) used also ARIMA (2, 1, 0) and ARIMA (0, 1, 1) for prediction of solid waste amounts. The results of both studies indicated ARIMA (1, 1, 1) as the most appropriate model for the forecast of solid waste generation. Regression modeling was implemented in Waste Prognostic Tool and time series analysis (ARIMA and seasonal exponential smoothing) by Rimaityte et al. (2012) to predict municipal solid waste generation in Kaunas, Lithuania. They demonstrated that time series analysis is very suitable for short-term prediction of the waste generation (weekly variation). In order to describe and forecast the municipal solid waste fractions generation seasonal behavior for four East European cities, Denafas et al. (2014) applied time series analysis as well. A seasonal Auto Regressive and Moving Average (sARIMA) methodology was applied by Navarro-Esbri et al. (2002) for waste prediction. They demonstrated that sARIMA provides good results for daily and monthly data. Abbasi et al. (2013) proposed a new method of municipal solid waste forecasting based on application of support vector regression and data reduction.

Therefore, there is a perpetual need for waste management planning, when reliable data on waste generation, factors which influence waste generation and forecasts of waste quantities based on facts are obviously necessary. In this context, the aim of our paper is to provide and apply modeling tools to help the decision and policy makers and stakeholders in forecasting the amount of municipal solid waste fractions (paper and cardboard, plastic, glass, metals, biodegradable waste and others). In this purpose we have collected data for Iasi city, Romania such as: *the number of inhabitants*, *population aged 15 to 59 years*, *urban life expectancy* and *amounts of municipal solid waste generated* for the following years: 1990, 2000–2014 (16 years in total). The data used are at municipality level and are presented and illustrated in the Section 2 of the paper. The first three categories of data were collected from Iasi County Statistics (INS, 2015), while the amount of municipal solid waste and composition in Iasi were taken from data published by Doba et al. (2008) and Iasi County Council (2009). The age structure was chosen based on other studies which showed and proved that there is a positive relationship between the waste generation and the percentage of the medium age group (Beigl et al., 2005; Lindh, 2003). In fact, all variables were chosen based on other studies which demonstrated that these variables are linked with waste generation and have a greater influence than others (Beigl et al., 2005; Ordonez-Ponce, 2004; Rimaityte et al., 2012). After we studied other research papers and selected the variables, the data collection process was performed. If for the first tool (Waste Prognostic Tool) the variables were already fixed and required by the software, for the other one (Minitab) we have chosen from several variables those that provide results closer to the reality and certainly the same that we used for the first tool.

The estimated amounts of waste are based on the analysis of the relationship between socio-economic conditions and the rate of waste generation (Fig. 1). Data resulted from waste prediction is linked with waste generation, planning and exploitation of waste management system. From Fig. 1 it can be observed that waste prediction is performed based on waste amount and nature of waste (which have impact on environment, resources and human health), and on economic and social conditions. Waste quantities are estimated in order to take actions to prevent waste, improve current waste management systems and use data obtained (after projection) in modeling and simulation. By knowing waste fractions that will be generated and their quantities, we can propose waste treatment/disposal methods which can be included in different waste management systems and then we can evaluate the MSW systems proposed using life cycle assessment methodology for establishing the environmental impacts, cost-benefit methodology for determining the costs and benefits of implementing of these systems or applying multicriteria evaluation methods and others.

2. Municipal solid waste management in Iasi, Romania

Iasi is a city belonging to Iasi County, a part of the Region North East from Romania (Doba et al., 2008). The number of inhabitants has increased according to the INS data (Fig. 2a) (INS, 2015). Fig. 2b illustrates the population aged 15–59 years: the values of this indicator are between 60 and 70% for the time period studied. The urban life expectancy in the city has increased (INS, 2015) (Fig. 2c).

Municipal solid waste amounts increased (Fig. 2d) being determined by two reasons: a higher consumption of the population and a higher proportion of the population served by public health services in a centralized system (this was measured by the sanitation company and the municipality that have signed contracts with the population to collect waste produced by the last ones and depending on the number of residents containers with a certain capacity were given for every household newly registered in the centralized system) (Doba et al., 2008; Ghinea, 2012). MSW composition consists in *biodegradable waste*, which represents the fraction with the major percentage (approximately 50%), followed by *paper and cardboard*, *plastic*, *glass*, *metals* (Doba et al., 2008; Ghinea, 2012). The waste composition in the urban area in Iasi in 2008 is presented in Fig. 2e. In Iasi city, MSW is collected by a public company, and separate collection of waste is carried out usually for materials with high market values, mainly in pilot projects.

The mixed waste collected in Iasi until 2009 were landfilled at the old landfill Tomesti, which was closed in the same year, since the site did not comply with the legislation in force and environmental issues such as pollution of atmosphere, soil and water (Ghinea, 2012; Schiopu and Ghinea, 2013; Ghinea et al., 2014). Since 2009, a new landfill at Tutora was put into operation, where the landfill leachate is treated using a reverse osmosis system (Schiopu and Ghinea, 2013), which involves the presence of a solution supply source, a pre-treatment step, a high-pressure pump, reverse osmosis membrane modules, and in some cases, a post-treatment phase (Schiopu and Gavrilescu, 2010). Schiopu and Ghinea (2013) demonstrated that, for leachate with complex composition the reverse osmosis is an effective and feasible alternative to provide good efficiency of separation. In 2009, a sorting station began to operate at Tutora site, while in 2012 a composting facility started to work. According to the European Directive on waste landfilling, the amount of biodegradable waste landfilled must be reduced so as to reach: in 2006, 75% of the quantity produced in 1995; in 2009, 50% of the quantity produced in 1995; and in 2016 to 35% of the quantity produced in 1995 (EC Council Directive, 1999). However, landfilling is still the most common treatment method for solid waste in many countries (den Boerden Boer et al., 2005a; Ozeler et al., 2006; Liamsanguan and Gheewala, 2008; Ghinea and Gavrilescu, 2010b; Bjelić et al., 2015). In brief, the amounts of solid waste generated by the inhabitants from Iasi are collected by a public company which transports the solid waste to Tutora station (about 10 km from the city), where some of the quantities of waste are landfilled (most of them) and others sorted by waste fractions. The Environmental Protection Agency Iasi (EPAIS, 2014) identified an inappropriate management of wastes (collection, treatment, recovery and disposal) and proposed improvement of selective waste collection (glass, paper, plastic, biowaste), promotion of separate collection at source of biodegradable waste to produce compost, encouraging and equipping households with composting containers, expanding sorting station, finalization of compost station, building mechanical biological treatment station and others.

Since planning or improvement of solid waste management systems can be achieved by knowing the amount of waste that will be generated, in this paper we have applied two tools for forecasting municipal solid waste generation in Iasi, Romania: *Waste Prognostic Tool* and *Minitab*. The *Waste Prognostic Tool* is based on a regression model and was used exclusively to predict municipal solid waste generation. Description of this tool is performed in Section 3 of the paper. *Minitab* was applied in order to perform *regression analysis* (RA) (to determine the changes of response variable when a predictor variable changes) and time series - *trend analysis* (TA) (to forecast the dynamic of waste generation considering Iasi city as case study).

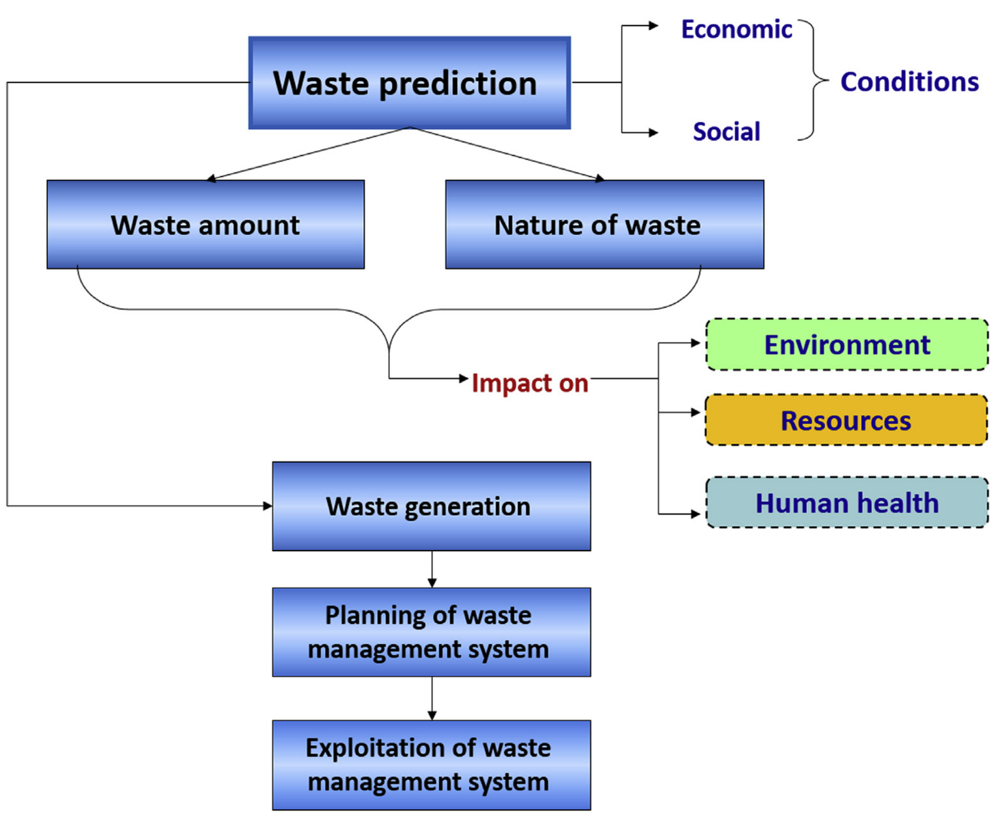

Fig. 1. Steps in waste management.

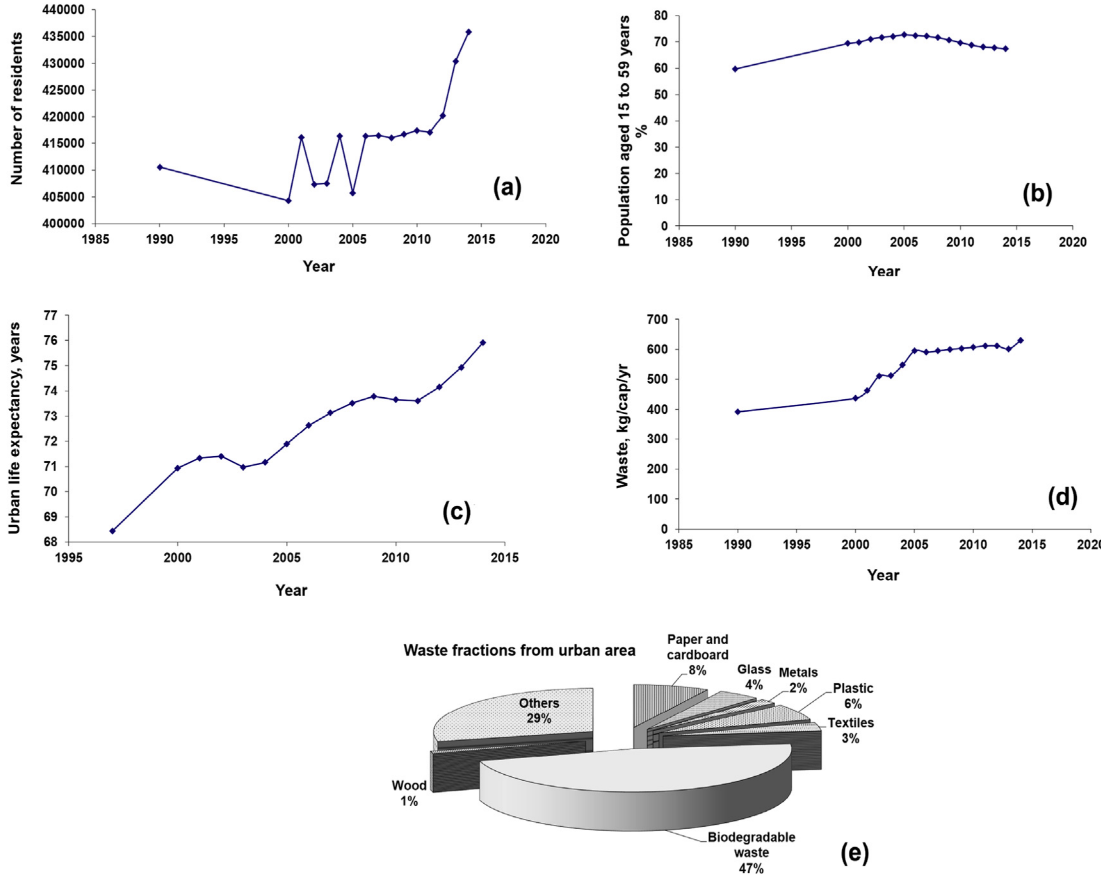

Fig. 2. Indicator values used for the analysis: a) number of inhabitants (INS, 2015); b) population aged 15–59 years (INS, 2015); c) urban life expectancy (INS, 2015); d) municipal solid waste (Doba et al., 2008); e) waste composition in Iasi in 2008 (Iasi County Council, 2009).

3. Waste Prognostic Tool

Waste prognosis is a key step in the adequate planning of waste management systems in different regions, under specific economic and social conditions which strongly influences the amounts of waste generated in different time frames (Ghinea, 2012; Oribe-Garcia et al., 2015). Due to its importance and complexity, computer based simulations of waste management systems were developed since the 1970s (Assefa, 2000). In this context, den Boer et al. (2005b) developed the software LCA-IWM Waste Prognostic Tool for the prognosis of waste quantities by waste fractions. Waste Prognostic Tool can be used for prediction of future amounts of generated waste in different cities based on a few input parameters. The factors that influence MSW dynamics are introduced as model parameters: population aged 15–59 years, infant mortality rate and life expectancy at birth, household size, gross domestic product per capita, labour force in agriculture (den Boer et al., 2005b; Ghinea and Gavrilescu, 2010a,b). This tool has already been applied to forecast municipal solid waste generation in some European cities (Beigl et al., 2004). Data about the municipal solid waste quantities were collected in 55 major cities in the EU15 and 10 CEE countries. The set of significant indicators which can predetermines the level of waste generation was discussed by Beigl et al. (2004) who also described the MSW generation model and the estimated equations for the final model. Waste Prognostic Tool was applied to predict the generation of solid waste in cities as: Xanthi (Greece), Kaunas (Lithuania), Wroclaw (Poland), Nitra (Slovakia) and Reus (Spain) (den Boer et al., 2005b; Rimaitytė et al., 2006; Tsilemou and Panagiotakopoulos, 2007). Subsequently to the prediction of MSW in these cities, various waste management scenarios were planned, which were evaluated using life cycle assessment tools developed by den Boer et al. (2005b).

Since Waste Prognostic Tool requires Microsoft Windows, Linux or Solaris OS; processor Pentium 166 MHz, 32 MB RAM; free hard-disk space 3 MB for application and 80 MB for Java we have ensured all these conditions in our laboratory.

Inputs parameters are: general information (name of the city, name of the country, number of city residents, reference year, assessment year), MSW quantities collected in the reference year (residual waste, paper and cardboard, glass, metals, plastics, bio-waste, garden waste and others in tonnes by year), percent by weight for each waste fractions, urban indicators (population aged 15–59 years, average household size, urban infant mortality rate, urban life expectancy), national indicators (gross domestic product per capita, national infant mortality rate, labour force in agriculture), projected values for urban and national indicators in the assessment year (including also the city population as urban indicator), waste prevention measures on municipal level (public and internal measures), planned separate collection performance in the city (collection rate for each waste fractions in %), while the outputs are: MSW generation forecast for each waste fractions and for total MSW in tons/year, kg/cap/year and % mass; MSW collection scenarios, planned MSW collection streams in the city.

The input parameters (MSW related parameters and development indicators) were introduced in the *Waste Prognostic Tool* which includes an econometric model (with a number of linear equations with up to four parameters) for cities or countries, which was adapted by those who developed it. Beigl et al. (2005)

considered forecasting analogous time series based on long-term development-related pattern changes and cross-sectional econometric models for each pattern regime for the development of the tool. The results are obtained based on log-linear regression model for MSW generation, while the prognosis horizon is defined as 10 years. The following calculation procedures are included in the tool: attribution of a region to a defined prosperity group in a future period (factors will be calculated using coefficient matrices), calculation of future MSW generation (actual value for the annual MSW generation serves as starting point for future waste quantity assessment and MSW changes are estimated on the basis of actual and future socio-economic conditions), assessing MSW composition.

We have applied Waste Prognostic Tool in order to obtain a prediction for municipal solid waste amounts that will be generated in Iasi city in 2023 (Fig. 3), by using the data existent in 2013. The quantities of solid waste generated by waste fractions in Iasi city in 2013 are important input parameters in achieving this forecast. The amounts of waste generated can be given by the tool for the assessed year 2023, but also for the reference year 2013 as t/year, kg/cap/year and % of mass. The socio-economic conditions were established using the database of Waste Prognostic Tool, which contains data derived from international organizations such as: United Nation, OECD, EU, World Bank, FAO, together with specific data for Iasi city.

Fig. 4 illustrates the composition of municipal solid waste as mass percentage until 2032. It can be seen a slight decrease of biodegradable waste content (2012–2032, Fig. 4), but this continues to be the fraction with the highest percentage, followed by paper and cardboard and plastics.

Waste prognostic tool is an instrument easy to use, which provide the results based on predefined indicators, the prognosis is made for the indicators values considered for the reference year and the forecasting is performed for the ten years.

4. Regression analysis

It is well known that the regression analysis can be used to determine how the response variable changes when a predictor variable changes (Minitab, 2014). In our case the input variables (the k factors) are: x_1 - number of residents, x_2 - population aged 15–59 years, x_3-urban life expectancy and x_4 - total municipal solid waste (t/yr). Regression investigates the relationship between a response (x_5 in our case) and predictors (x_1, x_2, x_3 and x_4, which are the input values in our case). In general it can be used for the evaluation 2^k different experimental conditions which represent all combinations of the k factors (Berthouex and Brown, 2002). For this evaluation we have considered a $k = 4$ factorial design, which means that a 2^4 design includes 16 runs to investigate four factors. The data collected for the time interval of 16 years were used as inputs variables.

In our analysis we considered the following output variables x_5 (each one at the time): e_1 *- paper waste,* e_2 *- glass waste,* e_3 *- plastic waste,* e_4 *- metals waste,* e_5 *- organic waste,* e_6 *– other waste*. The outputs were obtained based on the inputs values: $e_1 = f(x_1, x_2, x_3, x_4)$, $e_2 = f(x_1, x_2, x_3, x_4)$, $e_3 = f(x_1, x_2, x_3, x_4)$, …, $e_6 = f(x_1, x_2, x_3, x_4)$.

The parameter settings for the regression analysis are presented in Table 1.

We have performed the regression analysis with Minitab 17 software. In the first phase we have considered paper and cardboard waste as the response $e_1 = f(x_1, x_2, x_3, x_4)$. The data were introduced in software and, after modeling, we have developed a regression equation (Eq. (1)), which is an algebraic representation of the regression line and describes the relationship between the response and predictor variables (Eq. (2)).

$$Response = constant + coefficient*predictor + \ldots + coefficient*predictor \quad (1)$$

$$e_1^{0.5} = 73.17 + 0.000003x_1 + 0.1195x_2 - 0.0890x_3 + 0.000357x_4 \quad (2)$$

A Model Summary for Transformed Response was obtained (Table 2) were S, R^2 and *adjusted* R^2 are measures of how the model fits the data. S represents the standard distance that data values fall from the regression line: the equation predicts the response much better if S has a lower value. *R-Sq* or R^2 describes the amount of variation in the observed response values that is explained by the predictors, if R^2 is close to 100, the outcomes are better.

Adjusted (adj) R^2 is a modified R^2 that has been adjusted for the number of terms in the model. This indicator is useful in the case of the comparison of models with different predictor numbers. R^2 *predicted (pred)* is a measure of how well the model predicts the response, if there are large differences between this R and the other two statistics can indicate that the model is over fit (Minitab, 2014). In our case, for paper waste we have obtained $S = 0.191$, $R^2 = 99.98\%$, which means that our outcomes are better since R^2 is very close to 100 and S has a lower value.

Table 3 presents the analysis of variance for paper waste, which shows the variation amount in the data response explained by the predictors. The most important results to consider are represented by *p-values*. For interpretation of $p - value$, a α*-level* is used which commonly is 0.05. If for regression the *p-value* is 0.000 this indicates that at least one of the regression coefficients is significantly different than zero. For paper waste analysis, the *p-values* are 0.000 for x_2 and x_4 and different than zero for x_1 and x_3 but higher than α*-level*. This is characteristic to the other waste fractions evaluated in this study (plastic, glass, metals, biodegradable and other waste), being obtained the same values for p. This means that x_2 and x_4 (population aged 15–59 years and total municipal solid waste) are significant factors for the analysis, while x_1 and x_3 are less significant.

The *p-values* and *F-values* are the same for all solid waste fractions, differing only the values for adjusted sums of squares *(Adj SS)* and adjusted mean squares *(Adj MS)* (see the Annexes, Tables A1–A2). The sums of squares represent a measure of variation or deviation from the mean, while mean squares (MS) is an estimate of population variance which is calculated by dividing the corresponding sum of squares by the degrees of freedom. The mean squares are used in the regression to determine whether terms in the model are significant. *F-values* are calculated by dividing the factor *MS* by the error *MS* (Minitab, 2014).

Minitab software estimated the coefficients for each predictor variable based on our sample (case study). The size and direction of the relation from predictor and response variable are described by the regression coefficients. The static coefficient *SE Coef* estimates the precision. *T-value* measures the ratio between the coefficient and its standard error. The values of T are used by Minitab to calculate the *p-values*. The variance of a coefficient is influenced by the correlations between the predictors in the model.

One factor, namely *variance inflation factor* (VIF) shows how much the variance of a coefficient is inflated. If the VIF values are close to 1, this indicates that the predictors are not correlated; when 1 < VIF <5 the predictors are moderately correlated; if the values are greater than 5–10 (the predictors are highly correlated), this suggest that the regression coefficients are poorly estimated (Table 4) (Minitab, 2014).

Fig. 5a shows the residual plots for paper waste. A graphical

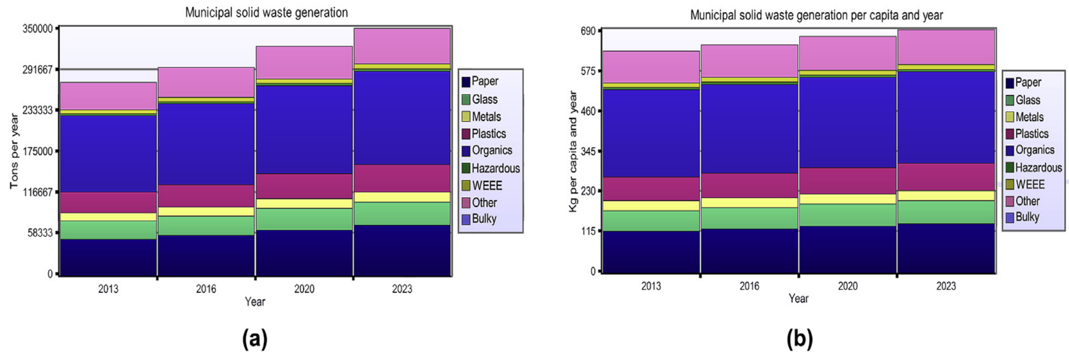

Fig. 3. Municipal solid waste generation a) tonnes per year; b) expressed as kg per capita and year.

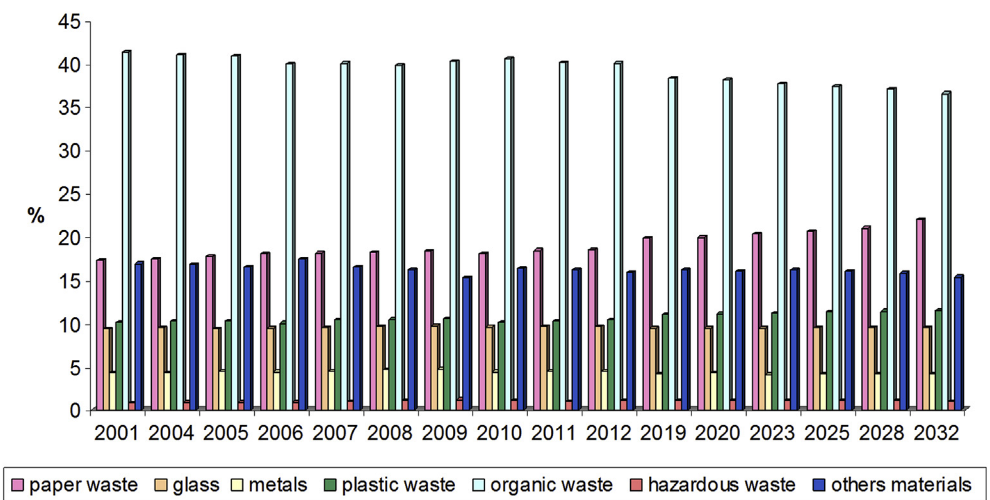

Fig. 4. Composition of municipal solid waste as mass percentage.

Table 1
Parameter settings for regression analysis.

Parameter	Value
Confidence interval	95
Type of confidence interval	Two-sided
Sum of squares for tests	Adjusted (Type III)
λ (for Box-Cox transformation)	0.5 (square root)

Table 2
Model summary for transformed response.

	S	*R-sq*	*R-sq(adj)*	*R-sq(pred)*
Paper waste (e_1)	0.191	99.98%	99.97%	99.87%

technique for evaluation of the distribution of data set is represented by the normal probability plot (Chambers et al., 1983). From this plot it can be observed if the data set is approximately normally distributed. When the points on this plot form a nearly linear pattern, this shows that the normal distribution is a good model for the data evaluated (NIST/SEMATECH, 2015). From Fig. 5a it can be observed that the points are very close to the line. The distribution of a univariate data set can be observed in a graphical representation as histogram (NIST/SEMATECH, 2015). Distribution of the residuals for all observations can be illustrated by a histogram of residuals (Minitab, 2014). In our case the histogram for paper waste (Fig. 5a) is bimodal (Doane and Seward, 2011), having the center

Table 3
Analysis of variance for transformed response – paper waste.

Source	*DF*	*Adj SS*	*Adj MS*	*F-Value*	*p-Value*
Regression	4	2076.77	519,194	14,142.89	**0.000**
x_1	1	0	0.003	0.07	0.789
x_2	1	1.06	1064	28.98	**0.000**
x_3	1	0.04	0.043	1.18	0.301
x_4	1	271.49	271,487	7395.34	**0.000**
Error	11	0.4	0.037		
Total	15	2077.18			

Adj SS - adjusted sums of squares; *Adj MS* - adjusted mean squares.
The bold figures in column *p* means that at least one of the regression coefficients is significant different than zero.

0 and the variability between −0.3 and 0.3: therefore there are no outliers.

The glass waste was considered as the response $e_2 = f(x_1, x_2, x_3, x_4)$. The evaluation was performed considering the same indicators (x_1 … x_4), the data were introduced in the software and after the analysis we have obtained the regression equation for glass waste, represented by Eq. (3):

$$e_2^{0.5} = 49.33 + 0.000002x_1 + 0.0806x_2 - 0.0600x_3 + 0.000241x_4 \quad (3)$$

The residual plots for glass waste are shown in Fig. 5b. It can be observed that, like in the case of the paper, waste regression analysis points for the normal probability plot are very close to the line. The variability is between −0.2 and 0.15, so there are no outliers (histogram plot, Fig. 5b).

The next solid waste fraction evaluated was plastic waste ($e_3 = f(x_1, x_2, x_3, x_4)$). Eq. (4) provides the regression equation obtained for plastic waste.

$$e_3^{0.5} = 69.76 + 0.000003x_1 + 0.1139x_2 - 0.0849x_3 + 0.000341x_4 \quad (4)$$

The histogram is bimodal (Doane and Seward, 2011), having the center 0 and the variability between −0.2 and 0.2: therefore, there are no outliers (Fig. 5c).

Also the metal waste, biodegradable waste and other waste were analyzed. The regression equations are the following: Eq. (5) for metal waste, Eq. (6) for biodegradable waste and Eq. (7) for other waste.

$$e_4^{0.5} = 54.04 + 0.000003x_1 + 0.0883x_2 - 0.0658x_3 + 0.000264x_4 \quad (5)$$

$$e_5^{0.5} = 157.6 + 0.000007x_1 + 0.2573x_2 - 0.192x_3 + 0.000769x_4 \quad (6)$$

$$e_6^{0.5} = 90.96 + 0.000004x_1 + 0.1486x_2 - 0.111x_3 + 0.000444x_4 \quad (7)$$

The residual plots for metal waste, biodegradable waste and other waste are presented by Fig. 5d, e, f. Graphics have almost the same shape, in particular those of residual versus fitted value and residual versus observation order.

The histogram (Fig. 5d) showed that the variability is between −0.2 and 0.2 for metal waste. In the case of biodegradable waste (Fig. 5e) the center is 0 and variability among −0.6 and 0.6, while for other waste the variability is between −0.3 and 0.3 (Fig. 5f).

In Table 5 there are shown the values for *S*, *R-sq*, *R-sq (adj)* and *R-sq (pred)* resulted after the analysis of each solid waste fraction. It can be observed that the values for *R-sq*, *R-sq (adj)* and *R-sq (pred)* are identical, very close to 100, whereas S values are different. The lowest *S* value is registered for glass waste (S = 0.129), while the highest, *S* = 0.412 was found for biodegradable waste. Since biodegradable waste has the highest percentage in the municipal solid waste composition, we have selected this indicator as response variable (x_5) and further we performed the evaluation to obtain the main effect plots, contour and surface plots. In Fig. 6 there are illustrated the main effect plots for biodegradable waste.

When we consider *urban life expectancy* (Fig. 6b, x_3 variable) the line is almost horizontal, which means that no main effect exists. In the case of the other variables analyzed, the response mean is not the same across all factor levels and it is considered that the main effect is present (Fig. 6a and b, x_4 variable) (Minitab, 2014). The magnitude of the principal effect is influenced by the steeper of the line slope. From Fig. 6 it can be concluded that *population aged 15 to 59 years* and *total municipal solid waste*, x_2 and x_4 variables strongly influences the *biodegradable waste*, followed by *number of residents* (x_1).

The contour plot is largely used to explore the potential relationship between three variables by displaying the three-dimensional relationship in two dimensions (Minitab, 2014). Fig. 7 illustrates the contour plots (lines) of biodegradable waste versus the four indicators (variables) used for analysis, by varying two variables together and holding constant the other two variables. Each plot shows the response surface at a pair of indicators (variables) considering that the third indicator is constantly maintained at the optimal value (Mathews, 2005).

The contour plots presented in Fig. 7 are characteristic to the first order model and the fitted response surface is a plane. The lines in the contour plots are parallel and they are almost straight (Myers et al., 2009).

The surface plots of biodegradable waste versus the four indicators studied are illustrated in Fig. 8. The response surface ($x_5 = f(x_1, x_2)$) showed by Fig. 8a is just a flat plane. It can be observed that various contours for x_1 (*number of residents* in our case) are all parallel to each other as are the contours for x_2 (*population aged 15 to 59 years*). The highest value of x_5 is in the upper right corner of the plot which corresponds with high values of both x_1 and x_2. The x_3 and x_4 are not displayed on the plot, Minitab holds the values of this two indicators constant $x_3 = 72.58$, $x_4 = 231746$ in order to calculate the fitted response values of x_5 (biodegradable waste in this case). The response surfaces from Fig. 8c, e and f look similar with these one.

It is very obvious that the response surfaces are with no curvature. From Fig. 8b it can be observed that the highest number of defects occur when the x_3 (*urban life expectancy*) has low values and x_1 (*number of residents*) high values. The surface is relatively flat across *urban life expectancy* which shows that the effect of this indicator is small compared to the *number of residents* influence (Mathews, 2005; Minitab, 2014). The same situation was found in the case presented in Fig. 8d: the surface is relatively flat, the highest number of defects occur when *urban life expectancy* has low values and *population aged 15 to 59 years* high values and it can be concluded that the effect of *urban life expectancy indicator* is small compared with *population aged 15 to 59 years* influence.

5. Time series - trend analysis

In order to achieve municipal solid waste prediction for Iasi city, Romania we also applied **time series analysis**. In the environmental studies the time series data are relatively common (Berthouex and Brown, 2002). The Minitab software provides four different trend models: linear (default), quadratic, exponential growth curve, or S-curve (Pearl-Reed logistic) (Minitab, 2014).

The resulted trend analysis for municipal solid waste was illustrated in Fig. 9. The graph presents three variables: actual (●), fits (■) and forecast (◆) versus time. The forecasting values were sets until 2030. For each type of model we have obtained one fitted trend equation. By using these equations, the predicted value at time *t* can be obtained. The fitted equations include the following elements: Y_t (the value of the variable measured at time *t*), *t* (time units) and coefficients (constants used to express the variable).

The Minitab software provide also values for mean absolute percentage error (MAPE), mean absolute deviation (MAD) and mean squared deviation (MSD). MAPE, MAD and MSD can be used to compare the fits of different forecasting (Minitab, 2014). MAPE measures the accuracy of fitted time series values in %, MAD

Table 4
Coefficients for transformed response − paper waste.

Term	*Coef*	*SE Coef*	*T-Value*	*p-Value*	VIF
Constant	73.17	5.52	13.26	**0.000**	
x_1	0.000003	0.000012	0.27	0.789	4.35
x_2	0.1195	0.0222	5.38	**0.000**	2.03
x_3	−0.0890	0.0819	−1.09	0.301	**9.49**
x_4	0.000357	0.000004	86.00	**0.000**	**7.63**

The bold figures in column *p* means that at least one of the regression coefficients is significant and different than zero; in column *VIF* the bold figures means that predictors are highly correlated.

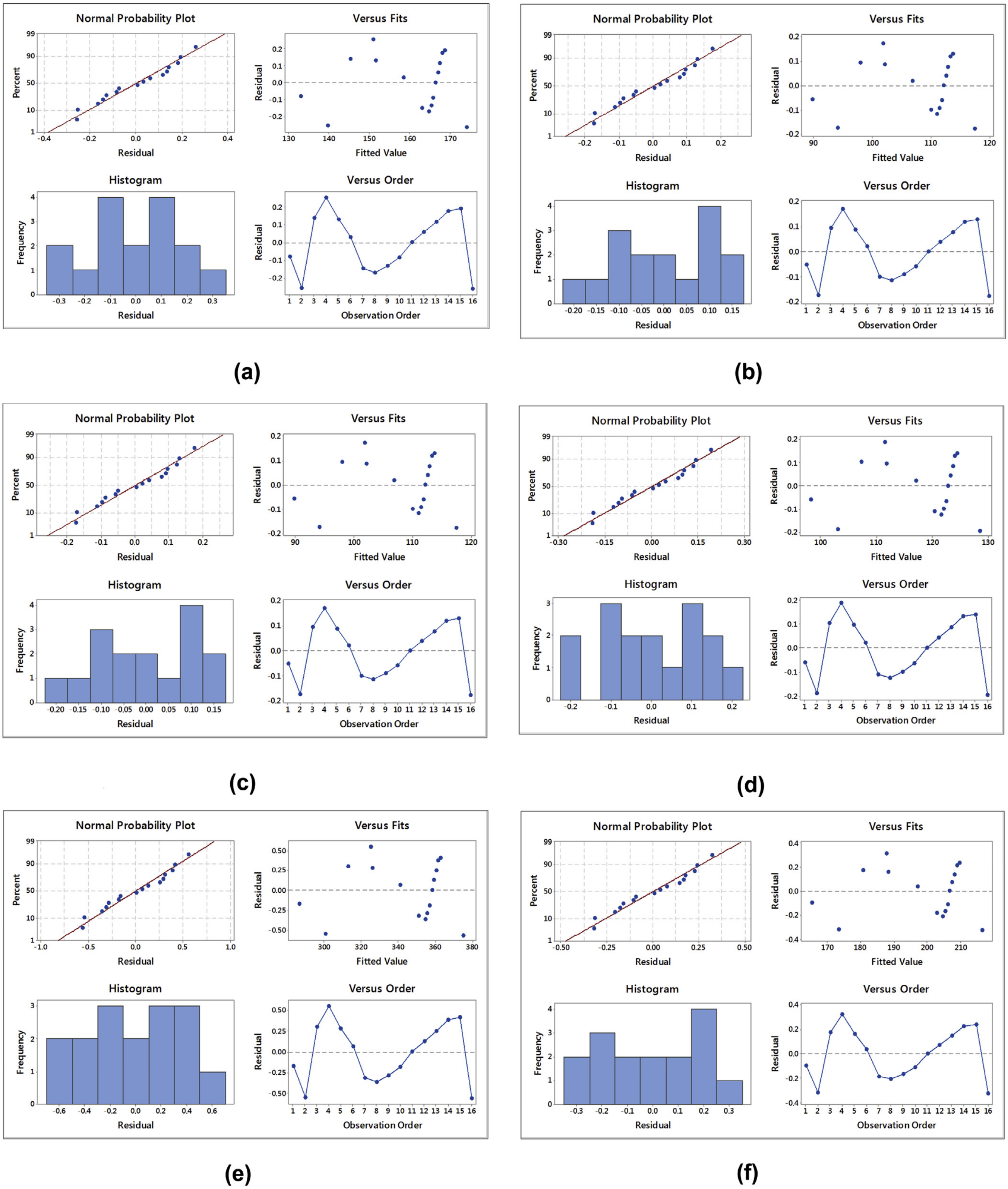

Fig. 5. Residual plots for waste: a) paper waste; b) glass waste; c) plastic waste; d) metal waste; e) biodegradable waste; f) other waste.

measure the same accuracy as MAPE, but in the same units as the data and helps to establish the amount of error, while MSD is calculated using the number of forecasts regardless of the model. Lower values for MAPE, MAD and MSD indicate a better fitting model (Minitab, 2014). In our case, lower values are registered for MAPE: 4% (linear trend model), 2% (S-Curve trend model), 5% (growth curve model) and 2% (quadratic trend model) (Fig. 9). S-Curve trend and quadratic trend have the same value of MAPE,

Table 5
Model summary for transformed response.

	S	R-sq, %	R-sq(adj), %	R-sq(pred), %
Paper waste (e_1)	0.191	99.98	99.97	99.87
Glass waste (e_2)	0.129	99.98	99.97	99.87
Plastic waste (e_3)	0.182	99.98	99.97	99.87
Metal waste (e_4)	0.141	99.98	99.97	99.87
Biodegradable waste (e_5)	0.412	99.98	99.97	99.87
Other waste (e_6)	0.238	99.98	99.97	99.87

smaller than MAPE values for the other two models. The S-Curve trend has the smallest MAD, while growth curve model has the highest value of MAD. Regarding MSD, high values were obtained for all models. The smallest value was recorded for S-Curve trend. It can be observed that S-Curve trend model is the most suitable for forecasting and it may provide better prediction values.

The trend analysis was also performed for each solid waste fraction. The equations obtained for each model are presented in Table 6. The forms of graphs were similar to those obtained for municipal solid waste illustrated in Fig. 9, therefore we presented in this paper only equations obtained for each fraction and also the accuracy measures (MAPE, MAD and MSD).

Analyzing the values of MAPE, MAD and MSD from Table 6, it can be observed that S-Curve trend model shows the most suitable model which can be used for prediction of municipal solid waste fractions considered. Comparing the S-curve and quadratic trends, we can see that: for paper waste, plastic, biodegradable waste and other waste the values for MAPE are equal (2%); for glass and metals are close; for all waste fractions the MAD values are close. Significant differences can be observed for MSD only. According to Kucharavy and De Guio (2007) the S-curve or logistic growth can facilitate an accurate forecast and reflects the action of a natural law, independently from scale and is relatively easy to apply, with a clear concept and can be used also for environmental changes and problem solving.

6. Discussion

The *Waste Prognostic Tool* is based on regression analysis and is an instrument which requires certain variables. This is useful in terms of setting variables, but we can not add other variables and we can not see what happens if we want to change one or more variables. In order to compare the results obtained with *Waste Prognostic Tool* we kept the same variables also for Minitab (using the most important ones and ultimately the variables which conducted to good results). We can say that the suitable tool for waste forecasting is *Minitab* which includes a number of techniques that can be applied to forecast the dynamic of waste generation, to determine the changes of response variable when a predictor variable changes and others. Compared with Waste Prognostic Tool which has a user friendly interface but require certain variables, that can not be changed, Minitab is more complex but it is easy to use and it can be added any desired variable and the results are most accurate. Another difference is that for Waste Prognostic Tool a large number of input data is needed, but for most of them the model already contains values.

The regression analysis was performed with Minitab 17 software and the regression equations were determined for each waste fraction considered in this evaluation (paper, plastic, glass, metal, biodegradable waste and other waste). The regression analysis is based on a factorial design of 2^4 type, which includes 16 runs to investigate four factors or variables. The results obtained showed that the values of R^2 were identical for all the waste fractions and very close to 100, while the values of S were different for each waste fraction, but with lower values which means that the outcomes are good. By investigating the p-values obtained with RA, we can conclude that the variables *population aged 15 to 59 years* and *total municipal solid waste* are significant factors for the analysis. We obtained the main effect plots, contour and surface plots for *biodegradable waste*, given the fact that this fraction has the highest percentage of waste composition. From the main effect plots it can be concluded that *population aged 15 to 59 years* and *total municipal solid waste* variables strongly influences the biodegradable waste generation.

With the help of Minitab (version 17) we also performed a time series analysis for prediction of municipal solid waste generation until 2030. By interpreting the values obtained for MAPE, MAD and MSD we can say that *S*-Curve trend model is the most suitable for municipal solid waste prediction for total waste and for each waste fraction evaluated.

The results obtained by us with Waste Prognostic Tool can be compared with other studies, for example: Denafas (2007) predicted municipal solid waste generation and fractions collection for Lithuania using Waste Prognostic Tool and observed that biodegradable content will be dominating until 2020, followed by paper and cardboard; den Boer et al. (2005b) and Rimaityte et al. (2012) showed that the quantities of solid waste vary significantly between regions and over time and their prognosis is usually aggravated by rapidly changing parameters of waste management systems.

Oribe-Garcia et al. (2015) used Minitab (version 16) to forecast solid waste generation based on regression technique, but they selected other variables. Time series analysis was valuable for Denafas et al. (2014) which applied this technique in order to assess

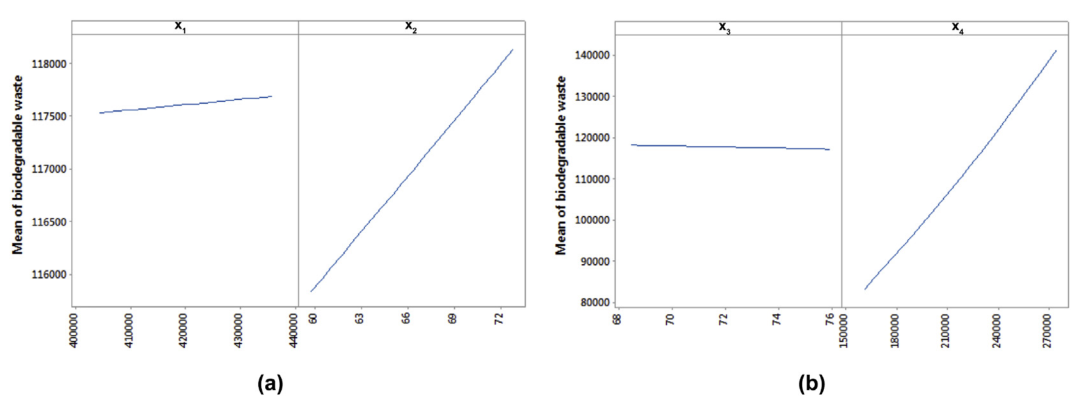

Fig. 6. Main effect plots of biodegradable waste.

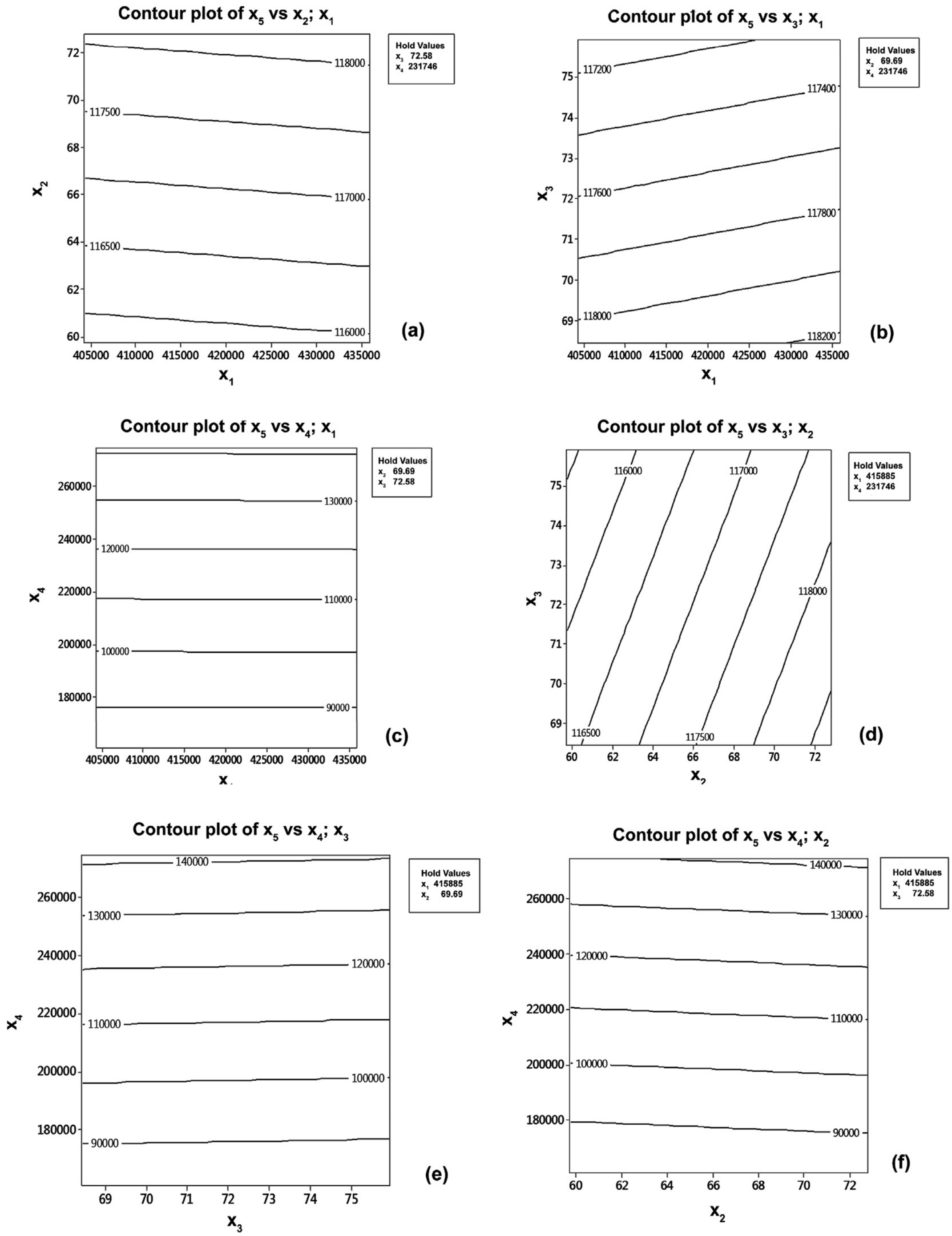

Fig. 7. Contour plots of biodegradable waste versus studied indicators: a) contour plot of biodegradable waste versus number of residents and population aged 15–59 years; b) contour plot of biodegradable waste versus number of residents and urban life expectancy; c) contour plot of biodegradable waste versus number of residents and total municipal solid waste; d) contour plot of biodegradable waste versus population aged 15–59 years and urban life; e) contour plot of biodegradable waste versus urban life expectancy and total municipal solid waste; f) contour plot of biodegradable waste versus urban total municipal solid waste and population aged 15–59 years.

the seasonal variations of waste generation, while Rimaityte et al. (2012) used it to forecast the weekly variation of waste generation data. Hussain et al. (2014) determined with Minitab (version 15) seasonal variations on generation rate and compositions of municipal solid waste in Lahore city and showed that the variations were significant only for organics, plastic and food waste. The results depend on the techniques and tools used and also on the chosen variables.

7. Conclusions

In this paper we applied two instruments: *Waste Prognostic Tool* and *Minitab* software in order to investigate and predict solid waste generation in Iasi, Romania. The following conclusions can be drawn:

- the prediction with Waste Prognosis Tool showed a slight decrease in the amount of biodegradable waste generated for

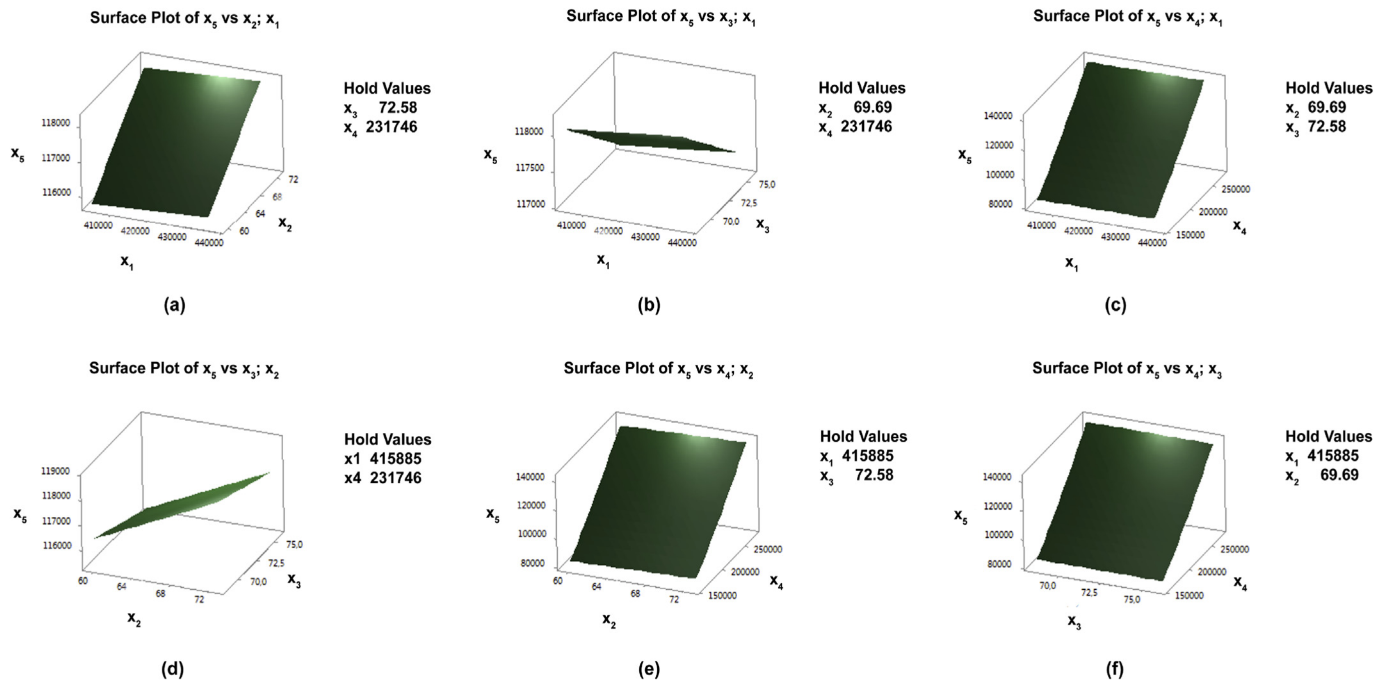

Fig. 8. Surface plots of biodegradable waste versus studied indicators: (x_1 - number of residents, x_2 - population aged 15–59 years, x_3-urban life expectancy and x_4 - total municipal solid waste (t/yr), x_2 - biodegradable waste).

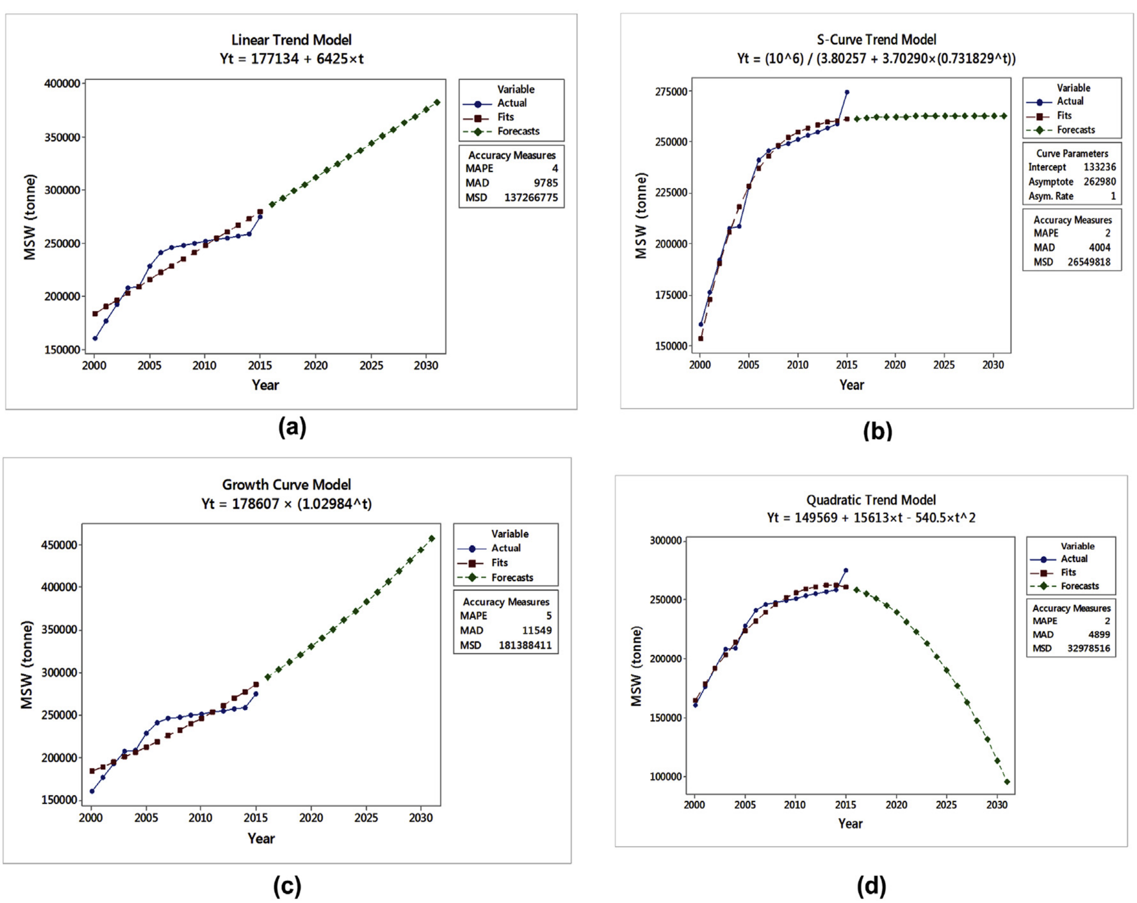

Fig. 9. Trend analysis plot for total municipal solid waste: a) linear trend model, b) S −curve trend model, c) growth curve model, d) quadratic trend model.

Table 6
Equations for analysis of waste fractions with different models and accuracy measures.

Waste fraction	Linear trend model	*S-Curve* trend model	Growth curve model	Quadratic trend model
Paper waste	$Y_t = 19485 + 706.8*t$ Accuracy measures MAPE 4 MAD 1076 MSD 1660928	$Y_t = 10^5/(3.456 + 3.366*(0.731^t))$ Accuracy measures MAPE 2 MAD 440 MSD 321253	$Y_t = 19646.8*(1.0298^t)$ Accuracy measures MAPE 5 MAD 1270 MSD 2194800	$Y_t = 16453 + 1717*t - 59.45*t^2$ Accuracy Measures MAPE 2 MAD 539 MSD 399040
Glass	$Y_t = 8857 + 321.3*t$ Accuracy measures MAPE 4 MAD 489 MSD 343167	$Y_t = 10^5/(7.605 + 7.405*(0.731^t))$ Accuracy measures MAPE 1.8 MAD 200.2 MSD 66374.5	$Y_t = 8930.36*(1.0298^t)$ Accuracy measures MAPE 5 MAD 577 MSD 453471	$Y_t = 7478 + 780.7*t - 27.02*t^2$ Accuracy Measures MAPE 2.1 MAD 245 MSD 82446.3
Plastic	$Y_t = 17713 + 642.5*t$ Accuracy measures MAPE 4 MAD 978 MSD 1372668	$Y_t = 10^5/(3.802 + 3.702*(0.731^t))$ Accuracy measures MAPE 2 MAD 400 MSD 265498	$Y_t = 17860.7*(1.0298^t)$ Accuracy measures MAPE 5 MAD 1155 MSD 1813884	$Y_t = 14957 + 1561*t - 54.05*t^2$ Accuracy Measures MAPE 2 MAD 490 MSD 329785
Metals	$Y_t = 10628 + 385.5*t$ Accuracy measures MAPE 4 MAD 587 MSD 494160	$Y_t = 10^5/(6.337 + 6.171*(0.731^t))$ Accuracy measures MAPE 1.8 MAD 240.2 MSD 95579.3	$Y_t = 10716.4*(1.0298^t)$ Accuracy measures MAPE 5 MAD 693 MSD 652998	$Y_t = 8974 + 936.8*t - 32.43*t^2$ Accuracy Measures MAPE 2 MAD 294 MSD 118723
Biodegradable waste	$Y_t = 90338 + 3277*t$ Accuracy measures MAPE 4 MAD 4990 MSD 35703088	$Y_t = 10^6/(7.456 + 7.260*(0.731^t))$ Accuracy measures MAPE 2 MAD 2042 MSD 6905608	$Y_t = 91089.7*(1.0298^t)$ Accuracy measures MAPE 5 MAD 5890 MSD 47179126	$Y_t = 76280 + 7963*t - 275.6*t^2$ Accuracy Measures MAPE 2 MAD 2499 MSD 8577712
Other waste	$Y_t = 30113 + 1092*t$ Accuracy measures MAPE 4 MAD 1663 MSD 3967010	$Y_t = 10^6/(3.802 + 3.702*(0.731^t))$ Accuracy measures MAPE 2 MAD 681 MSD 767290	$Y_t = 30363.2*(1.0298^t)$ Accuracy measures MAPE 5 MAD 1963 MSD 5242125	$Y_t = 25427 + 2654*t - 91.9*t^2$ Accuracy Measures MAPE 2 MAD 833 MSD 953079

2012–2030 period of time, but this will continue to be the highest percentage fraction of the total municipal waste generated, followed by paper and cardboard, and plastics;
- *Minitab* is more adequate for prediction, more complex, and also showing the data and plots in a much better view and correlation compared with *Waste Prognostic Tool*, which is a software special created for waste forecasting with variables already predetermined;
- the regression analysis can be successfully applied to determine the changes of response variable when a predictor variable changes;
- the variables *population aged 15 to 59 years* and *total municipal solid waste* are significant factors for the analysis and strongly influences the waste generation, while *number of population* and *urban life expectancy* are less significant;
- time series analysis is a technique which can be successfully applied for waste prognostic and in our case the *S*-Curve trend model is the most suitable for municipal solid waste prediction for total waste and for each waste fraction evaluated.

Since in this study we have conducted the RA considering social variables, in the following studies we will also consider economic indicators as variables which will replace the urban life expectancy variable that proved to have less influence on waste generation with gross domestic product per capita or other economic indicator. Also, models like ANN or ARIMA will be applied for municipal solid waste prediction in the next studies, in order to make a comparison of these tools and recommend the best one for decision makers.

Acknowledgements

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Annexes

Table A1
Analysis of Variance for Transformed Response for specific waste categories.

Source	*DF*	*Adj SS*	*Adj MS*	*F-Value*	*p-Value*
Glass waste					
Regression	4	943.988	235.997	14,142.89	0.000
x_1	1	0.001	0.001	0.07	0.789
x_2	1	0.484	0.484	28.98	0.000
x_3	1	0.020	0.020	1.18	0.301
x_4	1	123.403	123.403	7395.34	0.000
Error	11	0.184	0.017		
Total	15	944.172			
Plastic waste					
Regression	4	1887.98	471.994	14,142.89	0.000
x_1	1	0.00	0.002	0.07	0.789
x_2	1	0.97	0.967	28.98	0.000
x_3	1	0.04	0.039	1.18	0.301
x_4	1	246.81	246.806	7395.34	0.000
Error	11	0.37	0.033		
Total	15	1888.34			
Metal waste					
Regression	4	1132.79	283.197	14,142.89	0.000
x_1	1	0.00	0.001	0.07	0.789
x_2	1	0.58	0.580	28.98	0.000
x_3	1	0.02	0.024	1.18	0.301
x_4	1	148.08	148.084	7395.34	0.000
Error	11	0.22	0.020		
Total	15	1133.01			
Biodegradable waste					
Regression	4	9628.68	2407.17	14,142.89	0.000
x_1	1	0.01	0.01	0.07	0.789
x_2	1	4.93	4.93	28.98	0.000
x_3	1	0.20	0.20	1.18	0.301
x_4	1	1258.71	1258.71	7395.34	0.000
Error	11	1.87	0.17		
Total	15	9630.55			

(*continued on next page*)

Table A1 (*continued*)

Source	DF	Adj SS	Adj MS	F-Value	p-Value
Other waste					
Regression	4	3209.56	802.390	14,142.89	0.000
x_1	1	0.00	0.004	0.07	0.789
x_2	1	1.64	1.644	28.98	0.000
x_3	1	0.07	0.067	1.18	0.301
x_4	1	419.57	419.571	7395.34	0.000
Error	11	0.62	0.057		
Total	15	3210.18			

Table A2Coefficients for Transformed Response for specific waste categories.

Term	Coef	SE Coef	T-Value	p-Value	VIF
Glass waste					
Constant	49.33	3.72	13.26	**0.000**	
x_1	0.000002	0.000008	0.27	0.789	4.35
x_2	0.0806	0.0150	5.38	**0.000**	2.03
x_3	−0.0600	0.0553	−1.09	0.301	9.49
x_4	0.000241	0.000003	86.00	**0.000**	7.63
Plastic waste					
Constant	69.76	5.26	13.26	**0.000**	
x_1	0.000003	0.000012	0.27	0.789	4.35
x_2	0.1139	0.0212	5.38	**0.000**	2.03
x_3	−0.0849	0.0781	−1.09	0.301	9.49
x_4	0.000341	0.000004	86.00	**0.000**	7.63
Metal waste					
Constant	54.04	4.07	13.26	0.000	
x1	0.000003	0.000009	0.27	**0.789**	**4.35**
x2	0.0883	0.0164	5.38	**0.000**	**2.03**
x3	−0.0658	0.0605	−1.09	**0.301**	**9.49**
x4	0.000264	0.000003	86.00	**0.000**	**7.63**
Biodegradable waste					
Constant	157.6	11.9	13.26	**0.000**	
x1	0.000007	0.000027	0.27	**0.789**	**4.35**
x2	0.2573	0.0478	5.38	**0.000**	**2.03**
x3	−0.192	0.176	−1.09	**0.301**	**9.49**
x4	0.000769	0.000009	86.00	**0.000**	**7.63**
Other waste					
Constant	90.96	6.86	13.26	**0.000**	
x1	0.000004	0.000015	0.27	**0.789**	**4.35**
x2	0.1486	0.0276	5.38	**0.000**	**2.03**
x3	−0.111	0.102	−1.09	**0.301**	**9.49**
x4	0.000444	0.000005	86.00	**0.000**	**7.63**

The bold figures in column *p* means that at least one of the regression coefficients is significant different than zero; in column *VIF* the bold figures means that predictors are highly correlated.

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