A Review on Prediction of Municipal Solid Waste Generation Models

Adisa Inokon, Wilmin Bitala, Akaw Johnima, Ibrina Browndi
Department of Urban and Regional Planning, Rivers State University, Port Harcourt, Nigeria

ABSTRACT

Development of a Municipal Solid Waste Management (MSWM) plan is a complex process. As a foundation and prerequisite for efficient MSWM plan, quantification and prediction of Solid Waste (SW) generation is very much essentials. Municipal Solid Waste (MSW) prediction cannot be done directly and depends on so many factors. In actual practices, due to uncertainties and unavailability of sufficient data, modelling methods are needed for prediction of MSW generation. A number of researchers have predicted SW generation using various modeling methods. The main objective of this paper is to review such models related to MSW generation using economic, socio-demographic or management-orientated data and identify possible factors that will help in selecting the crucial design options within the framework of mathematical modeling. Five characteristic classification criteria, namely, modeling method, area covered, time series, independent variables and waste streams are focused in this review. The entire published models are diverse in nature for application from whole country to households. Successful modeling depends significantly on selection of waste stream. From the review and discussion of models the research aims to identify the limitations of previous models which will help in identifying the crucial design options within the framework of modeling. The study is concluded with a few fruitful suggestions.

KEYWORDS: Predictive Analysis, Urban Planning, Innovation Adoption, Machine Learning

1.0 INTRODUCTION

Solid Waste Management (SWM) is now one of the challenging issues for modern societies due to change in consumption pattern and uncontrolled urbanization and industrialization. Municipal Solid Waste (MSW) includes household, commercial, institutional, street sweeping, construction and demolition, and sanitation waste. MSW also contains recyclables (paper, plastic, glass, metals, etc.), toxic substances (paints, pesticides, used batteries, medicines), compostable organic matter (fruit and vegetable peels, food waste) and soiled waste (blood stained cotton, sanitary napkins, disposable syringes) (Sharholy et al., 2008). Global Waste Management Market Assessment (2007), reported 2.02 billion tones MSW generation globally and annual increase rate of 8% [1-5]. In India increasing urbanization and changing life styles, accelerate MSW generation in cities eight times more MSW than they did in 1947. About 90 million tons of MSW were generated annually (Sharholy et al., 2008). Per capita MSW generated rate increased to 1–1.33% annually (Bhide and Shekdar, 1998; Shekdar, 1999; Pappu et al., 2007). The composition and the quantity of MSW generated in India differ greatly with that in the western countries (Jalan and Srivastava, 1995; Shannigrahi et al., 1997; Gupta et al., 1998) particularly with hazards characteristics. Sharholy et al. (2008) mentioned that, MSW in urban areas contained large fraction of compostable materials (40–60%) and inert (30–50%). The relative percentage of organic waste in MSW was generally increasing with decrease in socio-economic status; so rural households generate more organic waste than urban households [6-10]. It has been noticed that the physical and chemical components of MSW depends upon a number of factors such as food habits, standard of living, degree of commercial activities, seasons etc. where the total MSW generation depends on total population. Effective collection and proper disposal of MSW depends greatly upon accurate prediction of generation of solid waste (Chang and Lin, 1997). MSW prediction cannot be made directly and depends on many qualitative and quantitative factors. Due to uncertainties and insufficient data availability, modeling methods were found to be beneficial. The main aim of this paper is to review the published models related to prediction of MSW generation. The limitations of the previous models were also discussed to identify the crucial design options within the framework of modeling [11-15].

2.0 LITERATURE REVIEW

Systematic reviews of various models on MSW prediction in this model may be regarded as an extension work of Beigl et al. (2008). The models related to waste generation upto 2005 were included in his work. This paper reviewed 20 MSW generation prediction models from 2006 to 2014 [15-20]. The waste generation prediction models are mainly based on decision –support system such as cost benefit analysis, multicriteria decision analysis and life cycle analysis [20-25]. The reviewed models may be classified into five broad categories based on: modeling method, study area, time series, independent variables considered and waste streams. Conventional waste generation prediction models including correlation and regression models generally used demographic and socioeconomic factors. Various independent variables were considered in most of the prediction models. However, a grey fuzzy dynamic model developed by Chen and Chang, (2000) was not based on any independent variable (except the time series data with at least three values) [26-30]. Some models used bivariate analysis (only one independent variable) whose validation depends on real MSW data such as correlation and regression analyses, time series analyses, and group comparison. These models expressed only cause and effect Other models used multivariate analysis (more independent variables) such as input output analysis, system dynamics, artificial intelligent system (fuzzy logic, artificial neural network, genetic algorithms) and multiple regression methods. These modeling methods create complications due to diverse interactions with the variables [30-35]. As a result validation of model becomes difficult. The models which were generally used to predict MSW generation within 2006-2014 are support vector machine (Abbasi et al. 2012), wavelet transform (Noori et al. 2009; Abbasi et al. 2012), artificial neural network (Noori et al. 2009; Abdoli et al. 2011; Antanasijevic et al. 2013), system dynamic (Kollikkathara et al. 2010;Chen et al. 2012), multiple regression analysis (Shan 2010; Dai et al. 2011; Keser et al. 2012), fuzzy logic (Karadimas and Orsoni, 2006; Lozano-Olvera et al. 2008; Oumarou et al. 2012), geographical information system (Purcell and Magette, 2009; Keser et al. 2012), single regression analysis (Ojeda-Benitez et al. 2008; Thanh et al. 2010; Lebersorger and Beigl, 2011; Li et al.2011), analytic hierarchy process (Li et al.2011), gray model (Liu and Yu, 2007) and time series analysis (Owusu-Sekyere et al. 2013; Mwenda et al. 2014). Consideration of large number of independent variables may increase cost of study due to requirement of large number of samples and long continuous database [35-40]. Therefore, it is essential to identify the data driven model (Noori et al., 2009). Among all the method mentioned fuzzy modeling handled the linguistic terms. Hence this method can work with quantitative and qualitative data. Fuzzy modeling approach is based on fuzzy rules which generate knowledge from data set and these fuzzy rules transfer knowledge to take proper decision. Also fuzzy logic system handles uncertainty of waste generation, insufficient dataset of samples and analysis of MSW successfully (Chen and Chang, 2000) [40-45]. Percentage wise, application of each modelling methods in 20 reviewed papers are presented in Figure 1. The study area considered by the modeling methods for prediction of MSW generation were mainly households and administrative units of districts since data were readily available and the application areas were comparatively smaller. Country wise data was also used in some models [45-50].

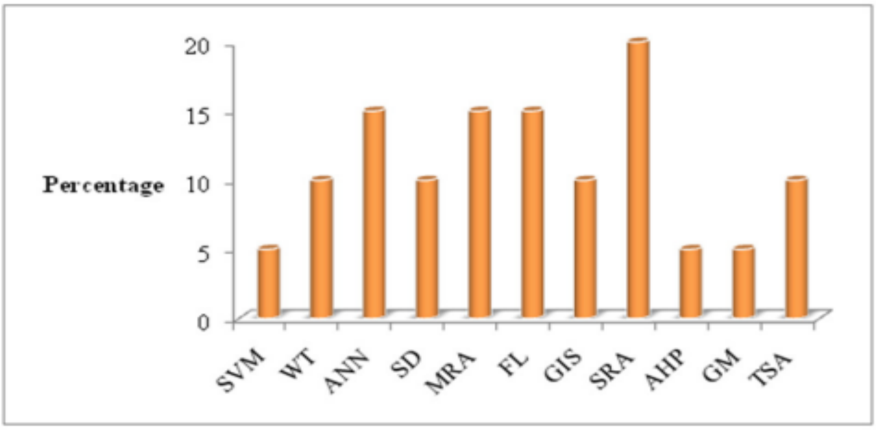

Fig. 1. Proportional use of modelling methods (2006-2014)

3.0 METHODOLOGY AND RESULT

In case of household related studies, relationship between individual habits and waste quantity, individual characteristics of the representatives of the household itself were analyzed. Depending on house type like single household, dwelling or an entire community, the sample sizes were ranged in between 50 to 100. MSW generation predication was based, mainly on income level (Lozano-Olvera et al., 2008; Ojeda-Benitez et al. 2008). However, weak correlation between income and household waste generation were also observed (Thanh et al. 2010). Thanh et al. 2010 revealed MSW generation was based on population density level of a household. Most of researcher acquired data through personal interviews and surveys. Individual level database were not available due to data protection issues of census (Lebersorger and Beigl, 2003). Hence prediction of MSW generation of a household becomes a difficult task In MSW prediction modeling the term districts includes the federal states (Purcell and Magette, 2009; Dai et al. 2011) or city (Liu and Yu, 2007; Noori et al., 2009; Kollikkathara et al., 2010; Shan 2010; Abdoli et al. 2011; Li et al., 2011; Chen et al. 2012; Owusu-Sekyere et al. 2013; Mwenda et al. 2014), city district, municipality and even part of city Area (Oumarou et al. 2012). Modeling is not just restricted to a particular city. But it covered also a significant number of small to medium sized municipalities (Lozano-Olvera et al., 2008; Lebersorger and Beigl, 2011; Abbasi et al. 2012), even electoral districts were considered (Purcell and Magette, 2009). Many studies covers annual time series length (Liu and Yu, 2007; Kollikkathara et al., 2010; Shan 2010; Dai et al. 2011; Lebersorger and Beigl, 2011; Li et al., 2011; Chen et al. 2012; Owusu-Sekyere et al. 2013), monthly, weekly and day wise (LozanoOlvera et al., 2008; Noori et al., 2009; Purcell and Magette, 2009; Abdoli et al. 2011; Abbasi et al. 2012; Mwenda et al. 2014) data. The studies which considered whole countries as study area, used data regarding total annual waste quantities, economic and census data from statistical department, trade associations and industry (Keser et al. 2012), gross domestic product (GDP) (Keser et al. 2012; Antanasijevic et al. 2013), total amount of material used directly in an economy (Antanasijevic et al. 2013) etc. MSW generation prediction models were mainly based on spatial distribution (Keser et al. 2012). Wide varieties of independent variables were considered in waste generation prediction models. Common independent variables which were considered are: population (Liu and Yu, 2007; Shan 2010; Thanh et al. 2010; Abdoli et al. 2011; Dai et al. 2011; Lebersorger and Beigl, 2011; Chen et al. 2012; Keser et al. 2012; Oumarou et al. 2012), income or GDP (Liu and Yu, 2007; Ojeda-Benitez et al. 2008; Shan 2010; Thanh et al. 2010; Abdoli et al. 2011), education (Ojeda-Benitez et al. 2008; Keser et al. 2012) age (Lebersorger and Beigl, 2011) etc. These variables were grouped as production, consumption and disposal related independent variables. Data related mass of product were rarely obtained. The retail sales were based as per market and national statistics (Liu and Yu, 2007). On the basis of consumption related independent variables, data of population and migrants creates more impact on waste generations (Shan 2010; Thanh et al. 2010; Abdoli et al. 2011; Dai et al. 2011; Lebersorger and Beigl, 2011; Chen et al. 2012; Keser et al. 2012; Oumarou et al. 2012).The other independent variables which were considered for modeling were: seasonal variation (Abbasi et al. 2012), total consumption expenditures (Dai et al. 2011), per capita municipal tax (Lebersorger and Beigl, 2011), income (Ojeda-Benitez et al. 2008; Thanh et al. 2010; Abdoli et al. 2011;), status of employment (Lebersorger and Beigl, 2011; Keser et al. 2012), urbanization (Lebersorger and Beigl, 2011) and consumption of gas, water, electricity (Liu and Yu, 2007) etc. Temperature and rainfall were also considered by Keser et al. (2012). Apart from the above mentioned independent variables, household data gives better results such as number of member (Ojeda-Benitez et al. 2008; Purcell et al. 2009; Lebersorger and Beigl, 2011) level of education or age groups (Ojeda-Benitez et al. 2008; Lebersorger and Beigl, 2011) and consumption habits of households (Dai et al. 2011). However, negative relation between number of members in house and waste generation were also observed (Thanh et al. 2010). Commercial establishment were also considered for modeling purposes (Purcell and Magette, 2009; Lebersorger and Beigl, 2011). The waste streams which were generally used for modeling purposes can be classified broadly into two types: material streams and collection streams. The material streams considered the product utilized for waste created by the consumers. This waste can only be determined through input output analysis. In modeling of waste generation prediction the data collected on material streams were used for validation purpose only since such data do not affect on model results. But in few research papers such data were used as dependant variables that are based on other input – output analysis (Kollikkathara et al., 2010; Li et al., 2011). Created wastes were not only by product utilized but also by packaging units used for various products (Lozano-Olvera et al., 2008). The collection streams considered methods of waste collections such as commingled waste, separated waste at source and other disposal options. Commingled waste generation data obtained from the official statistics were directly used for modelling (Kardimas and Orsoni, 2006; Liu and Yu, 2007; Ojeda-Benitez et al. 2008; Thanh et al. 2010; Abdoli et al. 2011; Dai et al. 2011; Abbasi et al. 2012; Owusu-Sekyere et al. 2013). Lebersorger and Beigl (2011) revealed that the chances of uncertainty and error in prediction process were increased in case of source separation. Single recyclable materials like glass, plastics, metals, paper and cardboard (Lozano-Olvera et al., 2008; Shan 2010; Thanh et al. 2010) separated at source were considered for modeling purposes. Residual wastes were considered by Lebersorger and Beigl (2011). Very few models considered other ways of disposal of wastes, like illegal use of solid waste for domestic fuel or domestic composting (Lebersorger and Beigl, 2011). Table 1 summarises the MSW prediction models used within 2006-2015. AHP- analytic hierarchy process, FLfuzzy logic, MRA- multiple regression analysis, ANN-artificial neural network, SD- system dynamic, SRA- single regression analysis, TSA- time series analysis, WT- wavelet transform, GIS- geographical information system, SVM- support vector machine, GM- gray model. HH- household, DS- districts, CY- country.CR-consumption related, DR-disposal related, PR- production related variables. CS-collection streams, MS-material streams.

4.0 CONCLUSION

Prediction of MSW generation plays a vital role in MSW management. A review of models on solid waste generation predictions showed that the overall size of the household, income level of households, and the level of education are most common attributes affecting the generation of waste. There is lack of official historical records of attributes affecting solid waste generation (both qualitative and quantitative) especially in developing countries. Since level of association between each of these attributes are not always same. So predictor in one level need not necessarily be a predictor in another. These are the main limitation on prediction of MSW generation. The entire published models are diverse in nature for application from county to households. Successful modeling is dependent significantly on selection of waste stream. Most of the models were based on correlation and regression analysis. Very few attempts have been made on artificial intelligent systems like fuzzy logic.

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