THE WROSE MODEL'S METHODOLOGICAL ASPECTS AND ITS FOUR LEVELS OF SUSTAINABILITY INDICATORS

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ABSTRACT: Waste management can become more complicated and require a holistic program that will incorporate all the technical, environmental, economic, social and political factors. However, these factors are often overlooked or difficult to consider all at once in solid waste management. Several waste management decision models are available for different countries these days. The majority of these decision support models are based on various methods such as cost-benefit analysis, life cycle assessment, environmental risk assessment, multi-criteria decision making, and environmental impact assessment. The SARCHI Chair in Waste and Climate Change developed the Waste to Resource Optimization and Scenario Evaluation (WROSE) model for the South African context using data from various studies conducted at the University of KwaZulu-Natal since 2010. WROSE is a decision-support tool that incorporates a mixed-integer linear programming mathematical model integrated with Life cycle assessment and Multi-Criteria Decision Analysis methodology. This paper aims to describe the further development and integration of the WROSE model's four levels of sustainability indicators and methodological approach. The use of South African data and the inclusion of several economic, social, environmental and institutional indicators make the model unique. The model advanced by including new emission factors for waste management technologies using IPCC guidelines and US EPA methodology; a new GHG emission factor for incineration, pyrolysis, gasification, plasma gasification, and anaerobic digestion has been developed for South Africa. The model will assist municipalities and the private sector in South Africa in implementing the Integrated Waste Management Plan (IWMP) to achieve zero waste and GHG emission reduction targets by applying appropriate waste strategies. Finally, the model will identify the most appropriate waste management scenarios based on various sustainability indicators, including environmental, economic, social, and institutional.

Keywords: Waste to Resource Optimization and Scenario Evaluation (WROSE), GHG emissions, Decision supporting tool, life cycle assessment, multi-criteria decision making (MCDA), Mixed-integer linear programming mathematical model

1. INTRODUCTION

The high rate of population growth, rapid urbanization, growing economy and improvements in standards of living have significantly increased the solid waste generation in the world, Particularly in developing countries (Dlamini, Simatele, & Serge Kubanza, 2019; Song, Li, & Zeng, 2015). However, there is often indiscriminate waste discarding without concern and constitute one of the most critical public

health and environmental challenges in African capitals (Okot-Okumu & Nyenje, 2011). According to the Intergovernmental Panel on Climate Change (IPCC) report, global warming increased since the middle of the 20th century due to the high concentration of Greenhouse gasses (GHG) As a consequence of deforestation and non-renewable energy source consuming, which has an adverse effect on socioeconomic and environmental problems, particularly in sub-Saharan Africa (Couth & Trois, 2011). Landfills are the major contributor to the anticipated increment of GHG emissions, which increase from 29% of emission in the year 2000 to 64% and 76% in 2030 and 2050 respectively in developing countries (Friedrich & Trois, 2011). The waste sector in South Africa contributes 4.3% of GHG emission and responsible for about 5% universally (Friedrich & Trois, 2016).

It is necessary to follow, on the part of waste managers, a sustainable approach to waste management and to integrate strategies that will produce the best practical option, and this is a very challenging task due to lack of financial resources, technology, human resources, weak institutional and policy framework in a developing country such as South Africa (Dlamini et al., 2019). Waste management can become more complicated and require a holistic program incorporating all the technical, environmental, economic, social and political factors. However, these factors are often overlooked or difficult to consider all at once in solid waste management. Municipal solid waste (MSW) management involves the collection and transportation of waste from its sources to processing plants where it can either be converted into biogas, electrical energy, and compost or recycled for reuse. The unrecoverable waste can either be disposed of directly from the waste sources or from treatment plants to landfills. Therefore, careful planning is essential in order to implement these strategies optimally.

The traditional waste management scheme was a concern on economic perspective only and ignored the social and environment effect (Minoglou & Komilis, 2013). Later on, several research studies proposed mathematical models to solve waste management challenges. Cheng, Chan, and Huang (2003) combined mixed integer linear programming method and multi-criteria decision analysis to determine best landfill sites and a waste-flow-allocation pattern with realistic computational effort in the city of Regina. Another study by Shirazi, Samieifard, Abduli, and Omidvar (2016) presented a linear mathematical programming model to optimize and determine the current transferring and processing units of a solid waste management system in Tehran. Whereas, by applying the model, the system improved by decreasing the number of transferring stations and processing units. Chinchodkar and Jadhav (2017) developed a mathematical model to support the decision making on MSW management to determine optimal transportation system. Moreover, the proposed model minimizes the cost of waste transportation in the city of Mumbai, India. Mavrotas, Skoulaxinou, Gakis, Katsouros, and Georgopoulou (2013) developed a multi-objective programming model as a decision support tool to provide adequate information for the decision makers concerning to reduction of GHG emission and cost for MSW management. The proposed model applied in Eastern Macedonia & Thrace, Greek region in order to assess different waste management scenarios to improve the MSW management. Similarly, Lee, Yeung, Xiong, and Chung (2016) developed integer linear programming and mixed integer programming mathematical model that considers waste flows between collection point, incinerators, landfills and replacement truck warehouses. The model designed aimed to provide valuable information for decision makers in Hong Kong waste management system.

Cristina Trois and Jagath (2011) used Waste Resource Optimization Scenario Evaluation (WROSE) model to assessed environmental effects of several waste management strategies and scenarios for two landfills: the eThekwini Mariannhill landfill and UMDM New England landfill in South Africa. Similarly, the model has been utilized to evaluate the Port AgriZone of the Dube Trade waste management practice, and examine different waste management frameworks to execute reasonable and completely coordinated waste management technique at their AgriZone, regarding to landfill size saving and treating organic fraction created at the DTP AgriZone (C TROIS, DA SILVA, CIBATI, ALI, & KISSOON, 2018). For the South African context, the Waste to Resource Optimization and Scenario Evaluation (WROSE) model was developed by the SARCHI Chair in Waste and Climate Change using various studies conducted at the University of KwaZulu-Natal (Kissoon, 2018; Reddy, 2016). However, there is a gap in updating the model, incorporating additional waste management technologies and indicators, and integrating discrete

models into a single model.

The objective of this study is a further development of the Waste Resource Optimization Scenario Evaluation (WROSE) model by integrating the current discrete algorithms into a single framework, using mix integer linear programming mathematical model and Multi-Criteria Decision Analysis Method (MCDA), which serves as a decision-supporting tool for South African municipalities. The proposed model will be able to evaluate a various waste management strategies and scenarios concerning on economic, environmental and social perspectives, and provide valuable information for the decision makers and engineers in waste management sector for planning and integrating optimal technology and waste management strategies.

1.1 Research question

How to integrate the WROSE's discrete models into a single mathematical model to serve as a solid waste decision support tool for South African municipalities taking into account economic, environmental, social and institutional considerations?

1.2 Aims and objectives

The aim of the study is further the development and integration of the WROSE model using a mixed-integer linear programming mathematical model integrated with Life cycle assessment and Multi-Criteria Decision Analysis technique as a single model to serve as a tool to evaluate various optimal waste management strategies regarding a reduction of GHG emission from South Africa landfills.

1.2.1 Objectives

- What mathematical models exist for maximizing solid waste management strategies?
- Evaluate and identify the gaps in the WROSE model.
- Apply the life cycle assessment (LCA) approach to develop emission factors for waste management technologies
- Update and develop new emission factor for waste management technologies.
- Apply Multi-criteria decision analysis (MCDA) to evaluate waste technologies

2. METHODOLOGICAL APPROACH

Text The WROSE model's further development is based on a mixed-integer linear programming mathematical model integrated with Life cycle assessment and Multi-Criteria Decision Analysis technique. The model's development used the IPCC 2006 guideline and US EPA methodological approach. Various waste-related data, including the South African electricity mix, the carbon content of waste material, energy consumption, and IPCC default data on dry matter content, fossil carbon fraction, and oxidation fraction, have been utilized.

2.1 Mixed integer programming mathematical model

Mixed integer programming mathematical model problems involve optimizing objective functions subject to one or more constraints. The essential step of the method is defining the objective function, constraints, adjustable variables and decision variables. This study's objective function represents the overall daily waste management strategy. The constraints include those linking costs, the equivalent GHG emitted by the system, social acceptability and legal requirements. The first component gives investment, waste handling expenses, and the income from waste products like refuse, derived fuel and energy. The second element provides the global warming potential, landfill space-saving, waste diversion Rate and

energy consumed. Jobs creation, health risks and public participation are considered the third element. The last component deals with environmental and energy legislation, financial, administrative regulation and license requirements. Types of waste and the number of treatment techniques will be considered adjustable variables.

2.2 Life cycle assessment (LCA)

Life cycle assessment (LCA) assesses the environmental impacts of a product, process, or system throughout its entire life cycle, beginning with the acquisition of raw materials and continuing through manufacturing, distribution, use, and possible reuse/recycling, and concluding with final disposal (Ghinea & Gavrilescu, 2010). Implementing LCA for waste management helps broaden the analysis's scope and provides a complete view of the entire system, along with all processes and environmental implications (Bala et al., 2021). In addition, the LCA study of the waste management systems is essential because its application may address the diverse effects of pollutant emissions that particular waste treatment technologies produce and reduce the use of natural resources (Stevanović-Čarapina, Stepanov, & Prokić, 2019) The LCA has been demonstrated to be a valuable decision support tool for waste management strategy and planning (Bala et al., 2021; Stevanović-Čarapina et al., 2019). It can be employed to identify environmental hotspots and possibilities for optimizing environmental performance across a product's life-cycle, informing decision-makers, selecting appropriate environmental performance indicators and marketing (Stevanović-Čarapina et al., 2019).

An LCA study consists of four steps (ISO 14044, 2006): aim and scope definition, inventory analysis (LCI), impact review (LCIA), and interpretation phase. In the aim and scope phase, the most significant decisions are defined, including the reason for performing the LCA, which processes will be included, which environmental concerns will be addressed, and the system limits and level of detail. The life cycle inventory describes all environmental inputs and outputs from all product system components. It implies obtaining the essential data to achieve the study's objectives. Environmental impacts are classified and analysed in the life cycle impact assessment phase. The evaluation translates inventory data into indicators for each effect category. Interpretation is the final step of the LCA process that leads to findings, suggestions, and decision-making following the scope definition.

2.3 Multi-criteria decision making (MCDA)

Multi-criteria decision analysis (MCDA) is a formal, structured, transparent decision-making methodology. It assists groups or individual decision-makers in exploring their decisions in the case of complex situations with multiple criteria. MCDA evaluates alternatives of the choices with the end goal of selection or ranking, using various qualitative and quantitative criteria with different measurement units.

There are four steps involved in the implementation of any technique for decision-making incorporating numerical analysis of alternatives: (Triantaphyllou & Mann, 1989).

- Identify decision criteria (indicators) representing the different measurements from which alternatives can be seen. In this study, there are four primary indicators these are environmental, economic, social and institutional. These key indicators include sub-indicators to analyse the development of various waste management techniques and scenarios to establish the optimal solution.
- Identify alternatives which satisfy the decision problem objective. These are available waste management technologies options: landfill, landfilling with gas recovery and electricity generation, composting, anaerobic digestion, recycling, incineration, pyrolysis, gasification and plasma gasification.
- Providing the relative importance of the criteria (indicators)
  Processing the numerical values to determine a ranking of each alternative.

This research employed the Analytic Hierarchy Process (AHP), which is one of the MCDA techniques. The core process in the method is constructing a hierarchy structure for the decision problem. It is suitable for complex problem which has finite criteria (Forman & Gass, 2001). Consequently, a Pairwise comparison will be applied to each hierarchical level of criteria and sub-criteria to determine the relative importance of the criteria (Chan, Wang, & Chung, 2013). Every AHP methodology uses ratio scale measurement. The pairwise comparison matrix to determine the relative weight employs a nine-point scale measurement that can convert the decision maker's linguistic value into a numerical value (Triantaphyllou & Sánchez, 1997). A n x m (where Cn is decision criteria and Am is alternatives waste management technologies) matrix will be constructed from the pairwise comparisons of alternatives within each criterion.

The decision matrix will be,

$$A_{ij} = \begin{bmatrix} a_1 & C_1 & C_2 & C_3 & \dots & C_n \\ a_2 & N_{11} & N_{12} & N_{13} & \dots & N_{1n} \\ a_3 & N_{21} & N_{22} & N_{23} & \dots & N_{2n} \\ & N_{31} & N_{32} & N_{33} & \dots & N_{3n} \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ a_m & N_{m1} & N_{m2} & N_{m3} & \dots & N_{mn} \end{bmatrix} \tag{1}$$

The last step in the method is ranking the alternatives; this will perform by utilising the vectors of criteria weights and the matrix of alternatives; hence ranking for each alternative is calculated using the following equation:

$$P_i = \sum_{j=1}^{n}(X_{ij}.W_j) \ for \ i = 1, 2, \ 3, \dots m \tag{2}$$

Where:
P_i is the preference for alternatives
X_{ij} is the preference value of ith alternative concerning to jth criteria
W_j is the criteria's weight, obtained from a pairwise comparison

The highest Pi value will be the best alternative, and the rest alternatives are also ranked according to Pi value.

3. RESULTS

Using IPCC guidelines and US EPA methodological approach, a new GHG emission factor for municipal solid waste and individual waste fractions for incineration, pyrolysis, gasification, plasma gasification and anaerobic digestion is developed for the South Africa context using various data. The total GHG emission factor from waste incineration is estimated by aggregating the emission sources from

waste transportation, non-biogenic CO2 and CH4 emissions and reduction from the electric utility sector. The formulation of emission factors for gasification is based on energy consumption for the pre-processing of refuse drive fuel (RDF), gasifier, collection and transportation of waste material, and energy recovered from the gasication process. Also, the South African GHG emission factor for transportation waste and electricity provision is included in the calculation.

The energy input and output approach applied to calculate the emissions factor for pyrolysis, the energy required during pre-treatment, the start-up of the pyrolysis processes, fuel consumption for collection and transportation of waste and ash/residues from the treatment plant, and energy recovery are all taken into account. A similar approach is employed to develop the emission factor for plasma gasification, collection and transportation of waste and slag, electric consumption for the plasma gasifier plant, and reduction due to electric generation are the emission source. The emission factor for anaerobic digestion was developed on a wet weight basis using the same streamlined life cycle analysis method as the USEPA and IPCC 2006 guidelines. In the development of the emission factor, waste collection and transport to the AD plant, direct emissions from the plant operation, emissions and reductions from digestate application and substitution of inorganic chemical fertilizer with compost produced from digestate, and emission reductions from fossil fuel energy substitution due to energy recovery and electricity generation from waste are all considered.

Results from the mixed-integer programming mathematical model and MCDA enable the determination of the objective function, the constraints and decision variables and construct a decision matrix which evaluates alternatives of the choices with the end goal of selection or ranking, using various indicators (criteria).

4. CONCLUSIONS

This research study attempts to illustrate the methodological approach used to further develop the Waste to Resource Optimization and Scenario Evaluation (WROSE) model. New GHG emission factors have been developed for waste management technologies, such as anaerobic digestion, incineration, gasification, pyrolysis and plasma gasification, which were not included in the previous version of the WROSE model.

The mixed integer programming mathematical model and MCDA allow the model to review the proposed waste management technology alternatives of the choices with the end goal of selection or ranking. MCDM technique assesses various qualitative and quantitative criteria with different measurement units. Due to the research study is not completed, only a few outcomes are presented in this paper. In addition, the model's reliability and validity should be tested using a case study of South African municipalities' landfills data, which will occur upon completion of the research project.

The proposed model will be able to evaluate various waste management strategies and scenarios once the research has been completed. The waste management strategies will be evaluated based on economic, environmental, social and institutional perspectives, and it provides valuable information for the decision-makers and engineers in the waste management sector for planning and integrating optimal waste management strategies. The future research study aims to develop additional emission factors for waste technologies and incorporate various indicators to assist decision-makers in developing integrated programs for implementing solid waste management alternatives.

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