Waste-to-Energy Technologies for Slum/Informal Settlements in Nigeria

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Slum/informal settlements are an integral part of a city, with a population projected to reach 3 billion by 2030. It is also expected that the rate of waste generation will more than triple by 2050 in the cities of low-income countries of sub-Saharan Africa. At this rate, the risk to the environment and health of inhabitants are enormous, because the current waste management practices are not guided by legislation on proper use and disposal.

waste to energy PROMETHEE MCDM informal waste slum electrification

1. Introduction

The major challenge of this era is rapid urbanization and, by the year 2050, 66% of global population will reside in cities and urban areas [1]. In the periphery and inner parts of the cities, slum/informal settlements exist that emerge from the influx of people who travel to these cities to benefit from their growth and development. These settlements are generally characterized by low-income households, with zero compliance with planning regulations and poor access to electricity infrastructure on a daily basis [2][3][4].

According to the United Nations descriptive report on sustainable indicators, the number of people living in slum/informal settlements reached about 1 billion in 2018 [1]. When cities grow and develop from the consumption of materials, energy, and natural resources, more waste is generated, which has adverse effects on the environment [5].

The global waste generation rate is recorded as 2.0 billion tonnes of municipal solid waste (MSW) every year and, at the rate of 0.267 tonnes per capita, it can be deduced that 267 million tonnes of solid waste is obtained from informal settlements [1][6]. By 2050, the informal settlement population is projected to become 3 billion, which also implies that 801 million tonnes of municipal waste will be generated; this equates to 26.7% of the total waste projected to be generated globally (3.40 billion tonnes) [6]. In Nigeria, the total waste generated is 25 million tonnes per year, with an average per capita generation rate of 0.55 kg per day [7].

Sub-Saharan Africa, and the eastern and southern parts of Asia, are the fastest-growing regions for waste generation and informal settlement growth, where most of the waste management practices are below international standards in comparison to countries in the Organization for Economic Cooperation and Development (OECD) [8]. The problem of waste management in the developing regions will only worsen as urbanization rates increase; therefore, adequate waste handling measures must be put in place to abate the degradation of the environment.

The waste collection rate in these regions is about 26% in the cities and even less in the informal settlements. The majority of the collected waste is either burnt in the air or disposed of in open dumpsites without following proper regulatory standards [9][10][11].

In slum/informal settlements of low- and middle-wage countries, the waste is usually collected by street sweepers, scavengers, and local waste pickers who transport and trade waste with public and private sector municipal waste services. This is beneficial to the overall waste collection for the area; however, general disputes can arise between the informal waste collectors and the public/private sector when competition over waste collection occurs, thereby leading to the loss of livelihood, which impacts negatively on the overall waste collection rate [12]. It is for this reason that proper integration of informal waste pickers and formal sector waste collection services should be the top priority for municipalities, city planners, and energy policy makers.

The slum/informal settlements are often characterized by low access to electricity, so fossil fuel energy sources such as coal, firewood, and kerosene are often used to meet the energy demand from domestic activities, e.g., cooking and lighting in major households. The use of fossil fuels as an energy source contributes to global warming from the release of CO_2 gas into the atmosphere, making it necessary to seek cleaner fuel options [13].

Renewable energy sources such as urban solid waste, wind, solar, and hydropower have been identified as a means of providing sustainable energy sources for informal settlers. The problem of intermittency associated with the use of wind, solar, and hydropower to provide energy gives MSW an added advantage, since it is not affected by changes in weather conditions.

MSW refers to materials generally disposed of in urban areas, which include waste from houses, businesses, streets, and commercial and recreational centers. Generally, MSW consists of decomposable and non-decomposable portions [14][15][16]. The amount of energy that can be obtained from MSW is related to the quantity that is available and the efficiency of the conversion pathway. Other factors such as the population size and income level of a region or municipality are also important [17][18][19]. The factors that determine the amount of energy recovered from MSW are easily controllable, hence giving it a stable and predictable attribute as a renewable energy source to tackle waste issues, mitigate against global warming, and produce electricity that can be assessed by informal settlers.

2. Waste-to-Energy Technologies

Generally, waste-to-energy technology is capable of converting urban waste that is generated in the informal/slum settlements of GKUA to electricity through thermochemical and biochemical processes in a sustainable manner.

2.1. Description of Technologies

In this research, the four waste-to-energy technologies that were taken into consideration in the selection of the most appropriate for the GKUA are briefly described below:

2.1.1. Anaerobic Digestion (ANR)

This technology utilizes a biochemical pathway that recovers energy from waste through the putrefaction of organic matter in the presence of microbes in an environment with little or no oxygen to produce biogas. The biogas produced in the digester vessel is rich in methane (about 50–75%) and (25–50%) carbon dioxide, which can be used to generate electricity [20].

2.1.2. Landfill Gas Recovery (LFILL)

With this technology, landfill gas is produced from a landfill site in a biochemical process that follows the same principle as the anaerobic digestion technology. The landfill gas obtained can be used to generate electricity.

2.1.3. Incineration (INC)

This technology involves a thermochemical process where the urban solid waste is subjected to burning at high temperatures that range between 600 and 1200 °C [21][22][23]. The heat produced from the process can be used to generate electricity [14].

2.1.4. Gasification (GAS)

Gasification technology is a thermochemical process that converts waste with carbon content into syngas and other valued products at a high-temperature range between 750 to 1000 °C, with the aid of controlled air and steam. The syngas can be used to produce electricity [24][25][26][27].

2.2. Criteria Description

The criteria required for selecting the most appropriate waste-to-energy technology are based on technical, environmental, financial, and economic parameters [27]. For each criterion, there are sub-criteria, which are described in **Table 1** below:

Table 1. Sub-criteria description for the selection of the best waste-to-energy technology.

Criteria	Sub-Criteria	Description	Type of Factor	Unit
Technical	Electricity Generation (T1)	This is the yardstick used to determine the amount of electricity generated from waste.	Maximum/beneficial/positive.	kWh
	Efficiency (T2)	This measures the ability of the waste energy technology to convert all the energy produced effectively.	Maximum/beneficial/positive.	%
Economic	Investment Cost (EC1)	The technology that requires the least amount of	Minimum/non-beneficial/negative.	Million (USD)

Criteria	Sub-Criteria	Description	Type of Factor	Unit
		investment is preferentially selected.		
	Operation and Maintenance Cost (EC2)	The technology that has the least cost to operate and maintain is preferentially selected.	Minimum/non-beneficial/negative.	Million (USD)
	Cost of Energy (EC3)	The technology that produces electricity at the least cost is preferentially selected.	Minimum/non-beneficial/negative.	USD/kWh
Environmental	CO_2 Emissions (ENV1)	This measures the amount of carbon dioxide emitted into the atmosphere during the utilization of a given technology.	Minimum/non-beneficial/negative.	kt CO_2eq
Social	Land availability (S1)	This criterion measures the perception of available land space for productive use for the slum settlers after the construction of a waste-to-energy plant of any given technology.	Maximum/beneficial/positive.	Likert scale
	Community acceptance (S2)	This criterion measures the acceptance rate by the informal inhabitants of the given waste-to-energy technology.	Maximum/beneficial/positive.	Likert scale

The MCDM applies the use of criteria weights to attribute varying levels of importance, in order to filter the less preferred alternatives during the selection process. The significance of this is that, the bigger the weight, the more influential the criterion. The criteria weights determine the success of a decision-making process; however, a major challenge is the determination of the accuracy in its measurement. Generally, the weights of the criteria can be obtained either by a subjective or an objective method.

2.3.1. Subjective Weight Method

Subjective weights are determined by expert evaluation. These weights express the opinions of experts and are associated with bias and vagueness on the part of the decision maker. Examples of subjective weighting methods include Stepwise Weight Assessment Ratio Analysis (SWARA), Simple Multi-attribute Ranking, (SMART) [28], Analytical Hierarchy Process (AHP), Delphi, and Kemeny Median Indicator Ranks Accordance (KEMIRA) [29][30][31][32]. The bias in the judgment of the decision maker can be attributed to lack of experience and the insubstantial nature of the criteria. Some studies have explored the use of surrogate weights in eliciting methods to improve the decision-making process [33][34][35].

2.3.2. Objective Weight Method

Generally, objective weights consider the criteria values of the data array provided in the decision matrix. They are represented by mathematical equations, which determine their values without the input of the decision maker [36]. They are not as common as the subjective weight methods. Examples of objective weighing methods include Criteria Importance Through Intercriteria Correlation (CRITIC) [37][38] and ENTROPY [39][40][41]. Other examples include Criterion Impact Loss (CILOS) [42], Linear Programming Technique for Multidimensional analysis of Preference (LINMAP) [43], Integrated Determination of Objective Criteria Weights (IDOCRIW), and standard deviation [44]. The objective weights are employed to eliminate bias by carrying out a dispersion analysis of the criteria values in the data of the array [28].

Over the years, several studies involving MCDM made use of subjective and objective weights separately, without the inclusion of a common formula in the decision-making analysis. Biswajik [45] performed an analysis using Pythagorean fuzzy numbers with the TOPSIS method to eliminate uncertainties from the decision-making process. The AHP and entropy weights were used in a fuzzy MCDM to rank shipping companies [46]. Chung et al. [47] assessed the vulnerability characteristics of regional population size by considering the Delphi technique and Shannon entropy as subjective and objective weights, respectively.

2.3.3. Combined Weight (CWM)

To overcome the shortcoming of the above methods and improve the accuracy of criteria weight determination, the integration of subjective and objective weights into one single component was achieved using the integrated method proposed in the work of Ma et al. [48]. The integrated weight method is also supported in these studies [49][50][51]. However, Jahan et al. [52] proposed the combination weighting method after criticizing the accuracy of the integrated weight formula and noting the inconsistencies observed with the inclusion of objective weight values. The application of the combined weight formula can be found in these studies [53][54][55]. The combined weight method was tested on other MCDMs in the work of Vinogradov et al. [55]. Therefore, this research applied the combination weighting method to obtain an accurate measurement of the objective and subjective criteria.

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