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Evaluating Waste's Hazardousness using Fuzzy Logic and Simple Additive Weighting

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Abstract: It is vital to determine the most dangerous types of trash in terms of the environment and human health. The purpose of this selection is to make readers aware of the impact of garbage on the environment. As human knowledge of the environment grows, the utilization of garbage will naturally decrease. The goal of this research is to create a Decision Support Model (DSM) to decide which types of waste are the most dangerous. By integrating the Fuzzy Logic (FL) approach with the Simple Additive Weighting (SAW) method, the model takes into account six factors: Factory water waste, plastic waste, cloth waste, battery waste, electronic waste, and tube lamp waste. This model will be used by businesses that deal with information and technology, and in turn, it may be used to measure and rank waste, making it easier for readers to make key judgments such as which materials should be used less and which can do more harm to the environment and human health.

Keywords: Decision Support Model, Fuzzy Logic, Simple Additive Weighting, Most Hazardousness Waste, Waste, Bad Impact from Waste

Introduction

Waste has a detrimental impact on the environment and public health. Plastic trash, for example, that is disposed of carelessly by the community, has a detrimental impact. In addition to the habit of using plastic, the community should be aware of the negative consequences of the garbage they use, which will lead to new information about these consequences, as well as a reduction in usage and avoidance of littering.

Plastic trash, industry wastewater, battery waste, and fluorescent light waste were utilized in this investigation to establish the worst values under contaminated environmental circumstances (e.g., water, air, and soil). Also, to determine the worst value in human health problems, such as the risk of cancer, heart disease, and renal disease. Plastic trash and manufacturing effluent, which are generated daily, include several chemical compounds and heavy metals that are hazardous to the environment and have health impacts.

The substance or composition of samples, such as PAE, PCB, Ni, Pb, H_2S, Cu, Cr, NH_3, Hg, As, Zn, Cd, Li, Mn, Zn, Cd, Li. The samples used to determine the worst value of the harmful impacts of waste on the environment and health did not include all of the components.

It is expected that by conducting this research, a decision support conception will emerge in determining the worst impacts of the waste contained in the sample and that it will be able to assist society and researchers in determining the worst effects of plastic waste and factory wastewater on health risks and environmental risks. In this study, the fuzzy combined with Simple Additive Weighting (SAW) approach was used to create a Decision Support Model (DSM).

The samples used to calculate the worst value of the detrimental impact of trash on the environment and health did not contain all the components. It is intended that by doing this study, a decision support concept will be developed for determining the worst impact of the trash container in the sample and that it will assist the communities and researchers in determining the worst impact of plastic waste and industrial waste. There are both environmental and health concerns associated with drinking water. In this study, the fuzzy logic combined with the SAW technique is used to create a Decision Support Model (DSM).

Why does the Decision Support Model (DSM) so important in today's world? Because human decision-making isn't always correct; in fact, it frequently deviates, which can be caused by a variety of factors including unhealthy body conditions, feelings that make decision-making subjective, disturbances in the human environment, and so on (Amborowati and Wardoyo, 1979). Computer-based DSM, on the other hand, may make judgments based on strong logic, rationality, and objectives. The proper and accurate judgments will be made after numerous calculations of the current parameters.

SAW is a strategy that is often employed in decision support systems. The criteria for cases that will be addressed with the assistance of a decision support system require changes that are directly relevant to the issues at hand. Things that form the reference for selecting the criteria must be of high priority in connection to the problem to be solved. The number of criteria used to examine is not set, but the more versions of the criterion employed, the better the results.

Waste and rubbish have become a major concern today, with negative consequences for the environment and human health, yet there are still many individuals who are uninformed about waste and disregard it, resulting in numerous recycling breaches (Kurniawan, 2019). Because there are still a few individuals who believe and do not understand how hazardous trash is, it is anticipated that because of this research, more and more people would view waste as an important and serious problem. Many individuals are more eager to learn about garbage and how to properly manage it without hurting the environment since they are more scared and aware.

Based on the above context, and the relevance of evaluating waste's hazardousness using fuzzy logic, the study came to fruition. This is an expanded version of (Utama *et al.*, 2019) this study used Fuzzy logic combined with AHP and used four wastes as the sample (tube lamp waste, plastic waste, factory water waste, and battery waste).

SAW is often referred to as a sum-weighted method used in decision-making. This method requires a process of normalizing the decision matrix to a scale that can be used with all classes of available alternatives. SAW is a widely used technique for solving Multi-Attribute Decision-Making (MADM) problems. MADM is a method of finding the optimal alternative among several alternatives with specific criteria (Sahir *et al*., 2017).

Simple additive weighting can select the best option from a set of options; in this example, the alternative query is selecting areas damme. Dengue is endemic according to the parameters set forth. The provision of value, the value of the criteria and sub-criteria, and then the stage of evaluation criteria and sub-criteria will create a priority to define dengue-endemic region are all important factors in determining the weight of the priority selection (Noviarti *et al*., 2018).

The Simple Additive Weighting (SAW) technique, often known as a weighted summation method, is a weighted summation method. The Simple Additive Weighting method's core principle is to get a weighted sum of the performance of each alternative on each characteristic. The simple additive weighting approach was proposed for completing a settlement in the multi-process decision-making system. The simple additive weighting technique is a commonly used approach in making judgments with many characteristics, such that by implementing the SAW method on decision support systems, the completion of various decision-making procedures may be quickly completed (Nurmalini and Rahim, 2017).

One of the most often used strategies in decision support systems is Simple Additive Weighting (SAW). The selection of criteria for cases to be addressed with the assistance of a decision support system needs refinement that is directly tied to the issues at hand. Things that constitute the reference for determining the criterion should have a high level of urgency in relation to the problem to be solved. There are no fixed restrictions for the number of criteria used to analyze, but the more variants of criteria used, the better the findings will be [7]. Simple Additive Weighting (SAW), often known as weighted linear combination or scoring approaches, is a straightforward and widely used multi-attribute decision-making strategy. The weighted average is used in this procedure. An assessment score is produced for each option by multiplying the scaled value assigned to that attribute's alternative by the weights of relative importance directly provided by the decision maker, then summing the results for all criteria. This approach has the benefit of being a proportionate linear transformation of the raw data, which implies that the relative order of magnitude of the standardized scores remains constant (Afshari, 2010).

A decision support system with simple additive weighting method was utilized in this study to solve problems. The SAW technique has been widely utilized to assist in the solution of many difficulties in decision-making. Problems may be solved using a weighted ranking system. Because it is based on the value of the criteria and weighting that have been provided, it is expected to be a more exact evaluation with the ranking approach. This will result in more accurate results of the motorbike that will be picked by the consumer (Tanjung and Adawiyah, 2018).

Today, electronic waste is a big problem and has become a global problem. Because nowadays almost all parts of the country in this world use electronics for all the activities they do, such as smartphones, televisions, computers, gaming consoles, electronic chips, and motherboards. The survey stated that 200 tons of electronic waste were found on the banks of the river (Akuru and Okoro, 2010).

The existence of parameters and values utilized for computations that decide the decision support system's conclusion, it is stated, will never be ignored by the decision support system as a concept or technology. Typically, the data and information containing these values and parameters have been neatly kept internally, or it may have never been recorded previously and all of this must be ideally included in the decision-making process.

It's also claimed that parameters and values derived from current data or information can't be used if they don't make sense, or in other words, if they can't be processed using specific laws and regulations. To further process the existence of parameters and values in a data collection, optimization rules, statistics, and other analyses (including eustatic approaches) are usually utilized model (Utama, 2017).

This article explains the decision support model, which seeks to plan strategic production based on the product's cycle. This study not only uses DSM as one of the approaches, but it also employs fuzzy logic to select suppliers. The importance of decision-making in a business is highlighted in this article, thus DSM becomes a highly essential and useful asset in a company's operations. Making the correct judgments in the company will be profitable and produce profits while making the wrong decisions will result in losses. As a result, it is explained in this publication that DSM is utilized to reduce mistakes in SPP (payment approval letters) (Elysia and Nugeraha Utama, 2018).

This journal will address approaches and applications linked to intelligence decision-making in its advance in intelligent decision-making section. Artificial intelligence was utilized to build the method, which is beneficial for creating and implementing intelligent decision support systems. Decision support systems are a type of computerized information system that aids decision-making in a variety of fields, including agriculture, biotechnology, finance, banking, and so on. Making excellent and correct judgments is believed to be difficult (Lim and Jain, 2010).

Workers unloading effluents exposed to high amounts of PCDD/Fs, PBDE, and PCBs were also shown to have elevated oxidative stress indicators. TSH levels as a marker of altered thyroid function were also affected by occupational exposure to Polybrominated Ethers (PBDEs), a major BFR group, at e-waste sites; there was also an increase in the genotoxicity index in lymphocytes (micronuclei, binuclear cells) without even a concomitant increase in oxidative DNA damage (Yuan *et al*., 2008).

The graphic below depicts a list of chemical compounds included in electronic trash, as well as their effects on the environment and human health. This study also revealed that hospital waste contains a variety of chemical compounds, including PCDD/Fs, PBDEs, PCBs, PAHs, Al, As, Cd, Cu, Cr, Fe, Hg, Pb, and many more. It may be deduced from the several types of bad content found in electronic trash that the bad chemical content of e-wastes is extremely high and has a negative influence on health and the environment (Wen *et al*., 2008).

Electronic trash is one of the major sources of pollution throughout the planet. According to this magazine, Japan has the highest plastic trash, with 610 million pounds coming from computers (Kiddee *et al*., 2013). The United States came in second with a total of 500 million electronic trash, all of which fell into the same category, notably PCs. It also stated that e-waste disposal has two effects on human health: (a) Food chain issues, such as contamination by harmful chemicals from disposal and primitive recycling methods, which outcome in by-products entering the food chain and thus passing to humans; and (b) The direct impact on workers working in primitive recycling areas from their work exposure to toxic substances (Chan *et al*., 2007). In addition, several studies have shown that backyard recycling has a direct effect on workers. E-waste toxicity risks to human health, both chronic and acute, have emerged as a major social issue, as evidenced by case studies in China (Huo *et al*., 2007).

Textile waste comes from a variety of causes, some of which are inherent in the raw materials used and others which are related to inefficiencies in the production process. Because a flat two-dimensional fabric must be cut into irregular shapes so that the finished garment may be fitted to the three-dimensional human body, some waste is created, notably in the apparel and fashion industries. Aside from production waste, there is a significant issue with textile goods, most commonly garments, that have reached the end of their natural life. Whether it's due to inadvertent damage during usage, clothing wearing out over time, or just being thrown because they're no longer in style, a mountain of waste textiles quickly accumulates. In the United States and Europe, it is estimated that 10 m tons of textile waste from all sources is delivered to landfills each year. 1 Large amounts of garbage constitute a significant waste of economic resources and they may also have a substantial detrimental impact on the environment (Timmins, 2009).

Pollution generated by wastewater discharge is one of the most common kinds of pollution and one of the most detrimental to the world's coastal marine ecosystems. Most of the time, these waters are released along the coast in subtidal areas, where they might harm marine life. Their discharge into the natural environment is frequently connected with cellular and/or physiological abnormalities in species and habitat disturbance produced lasting alterations in community structure. Flora and fauna, like all living things, are vulnerable to the damaging effects of pollutants discharged into the environment (Redouane and Mourad, 2016).

Because of the ongoing changes in its characteristics and specificities, e-waste has been classified as one of the most problematic waste classifications to handle. Although developed nations recognize that recycling obsolete electronic equipment helps to protect the environment from dangerous substances, only 15% of e-waste created in 2014 was formally disposed of through nationwide take-back agreements. According to the United Nations Environment Programmer (UNEP), only 10% of the world's e-waste is recycled in affluent nations today, with the other 90% being transported to underdeveloped countries worldwide (Abalansa *et al*., 2021).

E-waste constituents fluctuate according to the manufactured goods and contain more than 1000 diverse substances, which fall under the 'hazardous' and 'non-hazardous' categories. Broadly, it includes ferrous and non-ferrous metals along with plastics, glass, wood, plywood, Printed Circuit Boards (PCB), concrete and ceramics, rubber, and other items. E-waste comprises about 50% of iron and steel followed by plastics (21%), non-ferrous metals (13%), and other constituents. Non-ferrous metals consist of precise metals such as Copper (Cu), Aluminum (Al), and precious metals, e.g., silver (Ag), gold (Au), platinum, palladium, etc., (Garlapati, 2016).

Materials and Methods

This research process (Fig. 1) begins with a preliminary investigation, defines the parameters and data, develops and analyzes the model, builds the model, and assesses it.

The first step in creating a DSM is to conduct a literature review to identify the major issues. The difficulty identified by this literature review is determining the most hazardous trash challenges (plastic, batteries, tube lamps, industries water waste, electronic waste, and cloth waste).

The research was carried out in three basic phases. The first step is to do a literature review. Several academic pieces of literature relating to the research issue were evaluated in this section. A literature database was used to locate them (e.g., sciencedirect.com). The construction of a model is the second stage. The major approach for developing a model was fuzzy logic that combined with Simple Additive Weighting (SAW). The dashboard of the model was also developed in the second stage. The built model is then tested in the last stage. The concept was eventually able to be tested through academic data analysis.

Two types of data are collected throughout the data collection process to get accurate and persuasive data: Primary and secondary data. Data acquired by performing interview research directly with specialists in line with the study's topic is referred to as primary data gathering. Interviews were used to gather parameters and data used in this study such as the weight that exists in each parameter that will be used when calculating the SAW value for each waste's parameter, the value of each chemical substance contained in the waste parameters,

Moreover, gathering information and data needed/gained from other written documents relevant to the research topic for secondary information. A literature review was used to acquire data from national and international scientific journals, e-books, theses, scientific papers, and books for this data analysis.

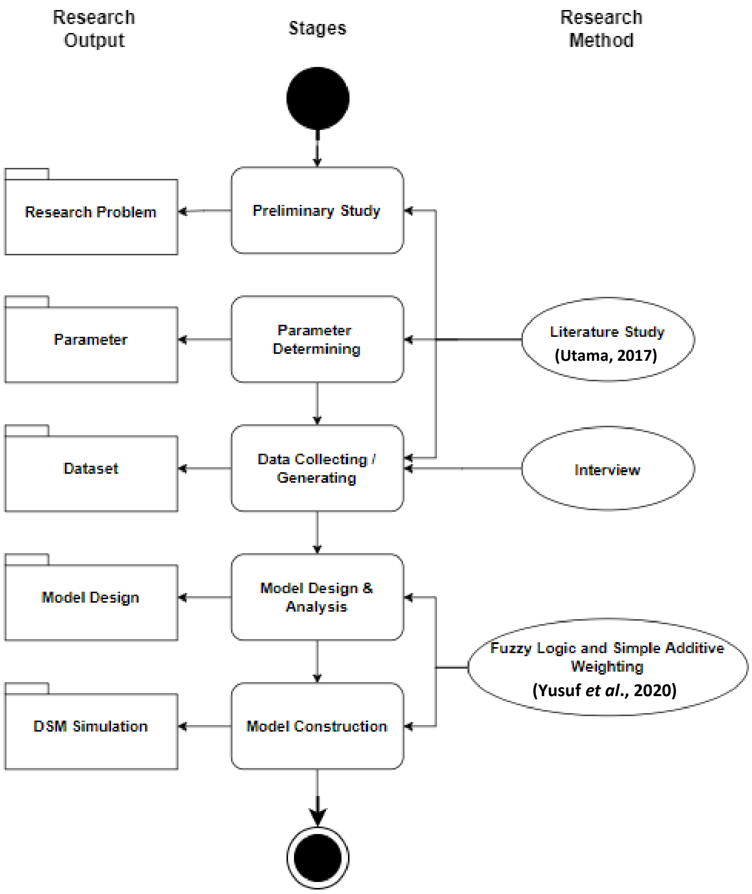

Fig. 1: Research methodology

In solving problems using fuzzy logic combined with the SAW method, several steps need to be done, there are as follows:

1. Determine the criteria that will be used as a reference in making decisions
2. Determine the suitability rating or weight for each criterion that we make
3. Create a decision matrix derived from the criteria that have been made
4. Normalization of the matrix described in the formula (1) using an equation tailored to the kind of attribute, a normalized matrix is generated. To obtain normalized values, (r_{ij}) is calculated as the criteria value (x_{ij}) Each criterion is divided by the highest value (benefit basis), and the minimum value of the criterion is divided by the value of each attribute (value basis):

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{MAX_i\left(X_{ij}\right)} \\ \dfrac{MIN_i\left(X_{ij}\right)}{X_{ij}} \end{cases} \tag{1}$$

5. The result is achieved by multiplying the normalized value (r_{ij}) with the weight value (W_j) or the formula can be seen in formula (2). The values for each criterion are then summed together. The winner is the option with the highest score:

$$V_i = \sum_{j=1}^{n} W_j r_{ij} \tag{2}$$

Results and Discussion

In this study, six parameters were used to determine the most hazardous waste that impacted the environment and human health. Factory water waste, cloth waste, batteries waste, electronic waste, plastic waste, and tube lamp waste. The constructed model will provide recommendations for the most hazardousness waste based on the highest point

The influence diagram (Fig. 2) will demonstrate how the model works; the technique will integrate fuzzy logic and simple adaptive weighting methods to reach the end aim of identifying the top people in the firm. All parameters are determined using FL techniques. The boundaries of each parameter are established using a fuzzy triangle membership function with specified linguistic variable constraints.

The kidney, water, leaver, cancer and water sub-parameters in the factory water waste parameters (Fig. 3) have five sub-parameters. These sub-parameters' values are derived from substances found in Factory Water Trash waste. Cu characteristics have a negative influence on the kidney, water, leaver, and cancer. Cr causes cancer and H_2S causes air pollution.

The air sub parameter of the cloth waste parameter (Fig. 4) is the only one. The value of these sub-parameters is derived from the chemicals found in cloth waste. CH_4 is one of the compounds found in cloth waste and it has a negative influence on human air quality.

The batteries waste parameter (Fig. 5) has 6 sub-parameters namely cancer, kidney, leaver, water, air, and soil. Where the value of these sub-parameters is obtained from chemicals contained in batteries waste. Li has a devastating impact on cancer, Cd and Zn have a bad impact on the kidney, Zn also has a bad impact on leavers, and As has a bad impact on water, air, and soil. Li has a devastating impact on water and soil.

Water, cancer, air, and soil are the four sub-parameters of the electronic waste parameter (Fig. 6). The values of their sub-parameters are derived from chemicals found in electronic waste. Mn has a negative influence on water, whereas Li causes cancer in humans and has a negative impact on the environment's air and soil.

The air and renal sub-characteristics of the tube lamp waste meter (Fig. 7) are both present. This is where the chemical components found in tube lamp waste are used to determine the value of both parameters. Li has a bruxing effect on the lungs and kidneys.

The plastic waste parameter (Fig. 8) has 4 sub-parameters including kidney, water, leaver, and cancer. This is where the value of both parameters is obtained from the chemical substances contained in plastic waste. Pb adversely impacts the kidney and liver, Ni and PAE adversely affect water, PCB, and Ni causing cancer in human health.

Each parameter has two linguistic categories namely moderately and extremely. For factory water waste, cloth waste, batteries waste, electronic waste, plastic waste, and tube lamp waste. Figure 9 has triangular bounds: (0, 0, 2, 6) and (2, 6, 10, 10).

Each parameter will contain many sub-parameters (Fig. 10) that will be utilized as input values for the assessment to determine its value. The first variable is water, soil, air, kidney, leaver, and cancer. The membership function is separated into two membership functions each parameter has two linguistic categories namely moderately and extremely. Have triangular boundaries: (0, 0, 2, 6) and (2, 6, 10, 10).

The sub-parameter value is obtained from chemicals (Fig. 11) contained in the parameters (factory water waste, plastic waste, cloth waste, batteries waste, and electronic waste). The chemicals are H_2S, Cu, Cr, NH_3 CH_4, As, Zn, Cd, Li, Mn, PAE, PCB, Ni, Pb, and Hg. The membership function is divided into three membership functions, namely equally, strongly, and extremely. With triangular boundaries: (0, 0, 2, 5), (3, 5, 7), and (5, 8, 10, 10). All parameters can be seen in Table 1.

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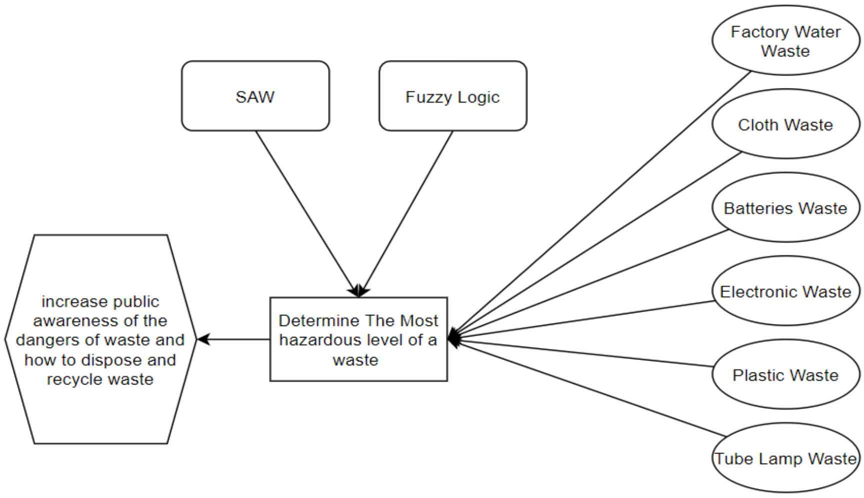

Fig. 2: Influence diagram

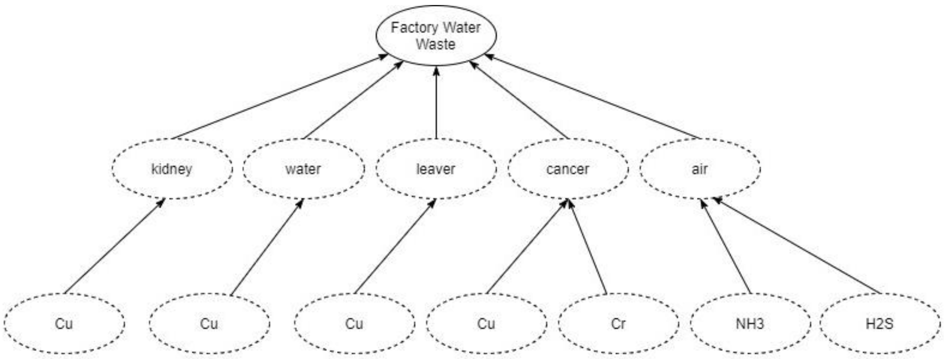

Fig. 3: Factory water waste parameter

Fig. 4: Cloth waste parameter

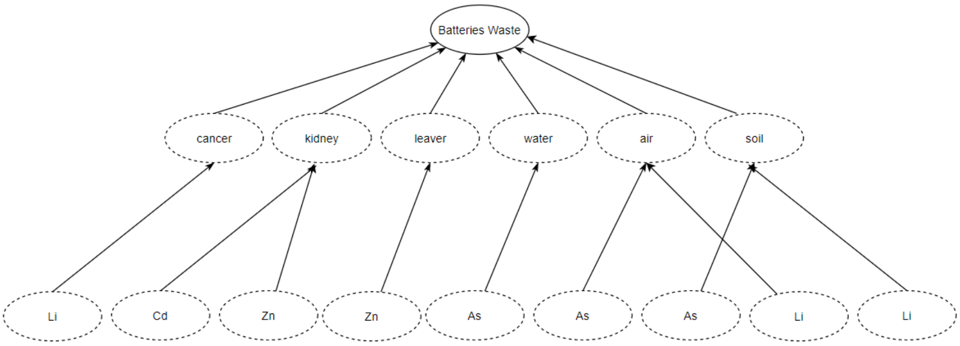

Fig. 5: Batteries waste parameter

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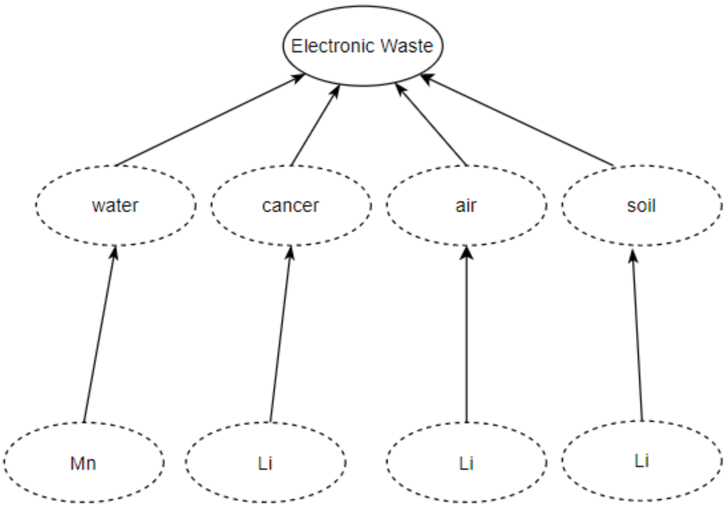

Fig. 6: Electronic waste parameter

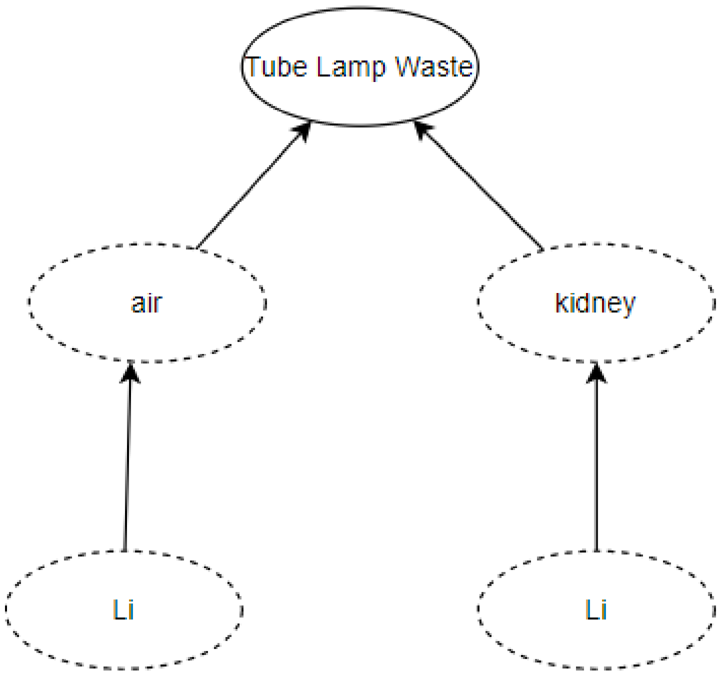

Fig. 7: Tube lamp waste parameter

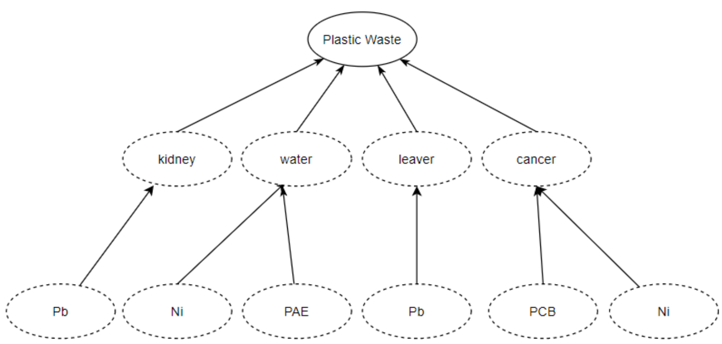

Fig. 8: Plastic waste parameter

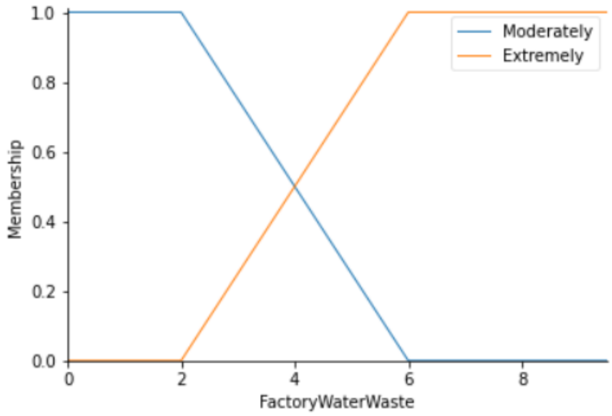

Fig. 9: Membership function for parameter factory water waste

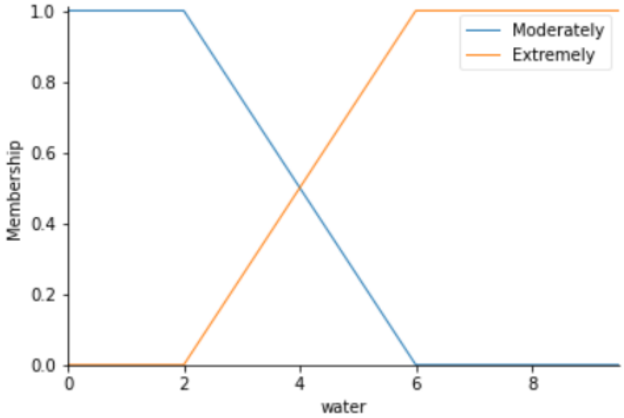

Fig. 10: Membership function for parameter water

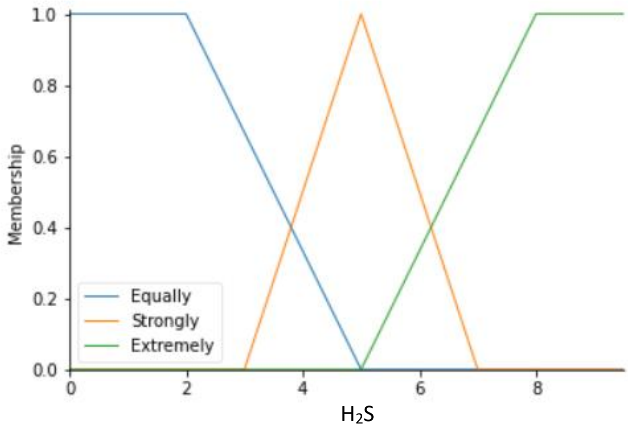

Fig. 11: Membership function for parameter H_2S

This stage's presence will explain the process of developing the model that will be produced in subsequent research; the explanation at this stage employs a class diagram (Fig. 12) as a tool to help readers comprehend and communicate the broad process of developing a hypothesis in this study. Classes, attributes, actions, and objects are all represented in the author's class diagram. The processes and linkages between classes that exist in the model that will be built in this study are depicted in this class diagram. Figure 9 depicts my model algorithm along with a class diagram based on my study and comprehension of the model I developed.

Factory water waste, plastic waste, batteries waste, and electronic waste got the highest weight value (Table 2). Because all of that parameters are more important to recycle based on the dataset that got from interviewing experts. Meanwhile, the hazardousness level is determined by chemical substances contained in the waste and by the impact that chemical give on the environment (air, water, soil) and human health (leaver, cancer, kidney).

Water got the highest weight value and follow by cancer and air in the second place and soil leaver and kidney in the last place with 1 weight value (Table 3). Because all those parameters got each of their important in giving an impact on human life.

The dataset got from interviewing experts that got an educational background in waste and chemicals and a work background in recycling waste. the dataset is used for determining how many weights value are used in the model and for each parameter value (Tables 4-9) for calculating the most hazardous waste in the model in this study.

The next step is to calculate the fuzzy value for each parameter (factory water waste, plastic waste, electronic waste, batteries waste, tube lamp waste, cloth waste) with the FL methid (fuzzyfying, defuzzifying) (Tables 10-15). The next step is to calculate using the first crisp output as the input value. The calculation has been calculated in the same way as the first crisp output using the FL method (fuzzyfying, defuzzifying). The calculation can be seen in Table 16. Furthermore, the values of each trash acquired by each waste will be combined so that it can be implemented in SAW (Table 17).

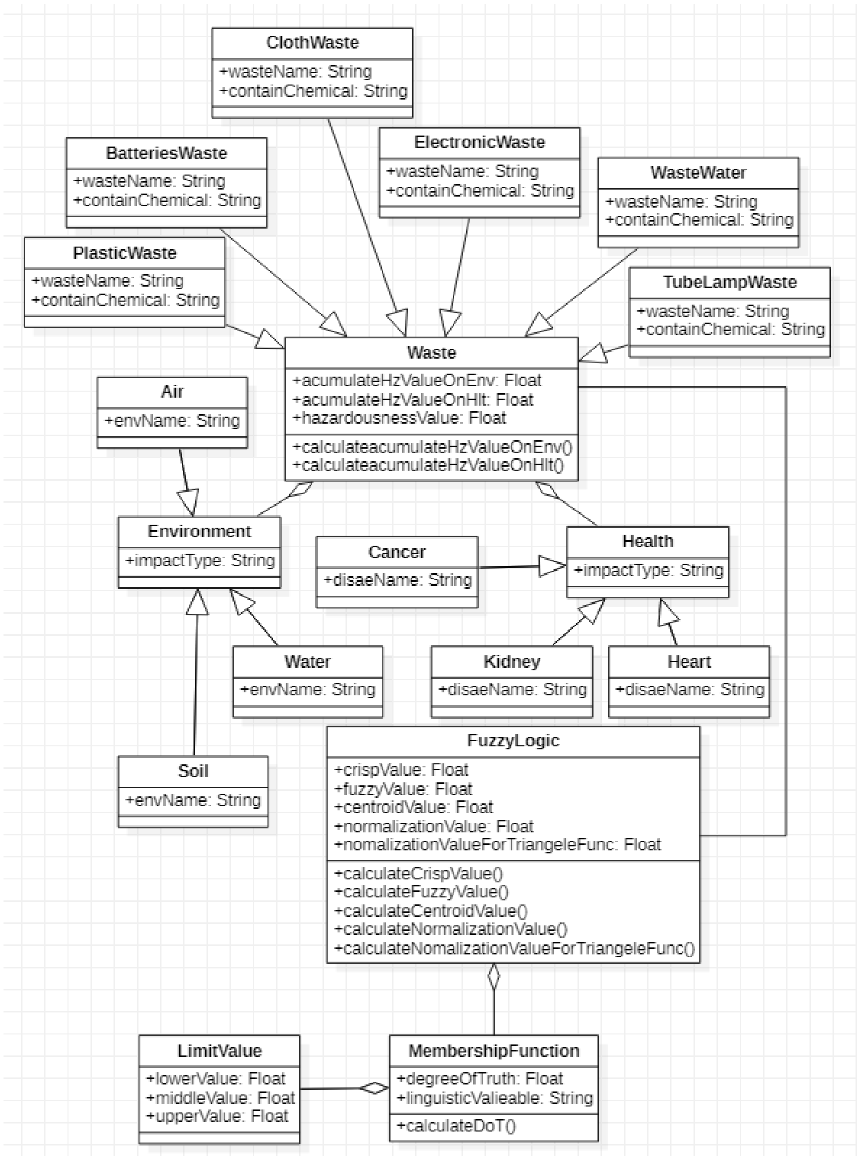

Fig. 12: Class diagram

If the weight of the parameter increases, the benefit criteria computation is utilized at this stage. Each waste's outcome is computed by multiplying the value of each parameter by a predetermined weight (Table 18). The findings of the rank computations (Table 18) will be used to provide the rank from the most hazardousness waste to the least hazardous. The most hazardous waste will be the one whose fuzzy logic and simple additive weighting computations yield the greatest value Table 18 demonstrates that electronic waste has the greatest total point score of 1.628, based on these total points, electronic waste is the most hazardousness waste compared to other wastes in this study.

Table 1: Parameter to determine the most hazardousness waste

Parameter	Sub-parameter	Chemical parameter
Factory water waste	Kidney	Cu
	Leaver	Cu
	Water	Cu
	Air	NH_3
		H_2S
	Cancer	Cr
		Cu
Plastic waste	Kidney	Pb
	Leaver	Pb
	Cancer	PCB
		Ni
	Water	PAE
		Ni
Electronic waste	Water	Mn
	Cancer	Li
	air	Li
	Soil	Li
Cloth waste	Air	CH_4
Batteries waste	Cancer	Li
	Kidney	Cd
		Zn
	Leaver	Zn
	Water	As
	Air	As
		Li
	Soil	As
		Li
Tube lamp waste	Air	Li
	Kidney	Li

Table 2: Weight for each main parameter

NO	Parameter	Weight
1	Factory water waste	2
2	Plastic waste	2
3	Batteries waste	2
4	Cloth waste	1
5	Electronic waste	2
6	Tube lamp waste	1

Table 3: Weight for each sub parameter

NO	Parameter	Weight
1	Water	3
2	Soil	1
3	Air	2
4	Leaver	1
5	Kidney	1
6	Cancer	2

Table 4: Sub parameter in factory waste

Factory water waste						
Water	Air		Kidney	Leaver	Cancer	
Cu	H_2S	NH_3	Cu	Cu	Cu	Cr
9	2	8	4	4	4	5

Table 5: Sub parameter in plastic waste

Plastic waste					
Kidney	Leaver	Cancer		Water	
Pb		PCB	Ni	PAE	Ni
1	2	1	1	2	4

Table 6: Sub parameter in electronic waste

Electronic waste			
Water	Cancer	Air	Soil
Mn	Li	Li	Li
10	1	9	6

Table 7: Sub parameter in batteries waste

Batteries waste								
Cancer	Kidney		Leaver	Water	Air		Soil	
Li	Cd	Zn	Zn	As	As	Li	As	Li
8	3	1	5	3	1	9	10	8

Table 8: Sub parameter in tube lamp waste

Tube lamp waste	
Air	Kidney
Li	Li
9	4

Table 9: Sub parameter in cloth waste

Cloth waste
air
CH_4
4

Table 10: Crisp output for factory water waste sub parameter

Factory water waste					
Water	Air		Kidney	Leaver	Cancer
8.17	1.17	7.01	5.17	5.07	4.75

Table 11: Crisp output for plastic waste sub parameter

Plastic waste				
Kidney	Leaver	Cancer		Water
2.16	2.16	2.16	2.16	3.15

Table 12: Crisp output for electronic waste sub parameter

Electronic waste			
Water	Cancer	Air	Soil
6.62	2.16	6.62	6.22

Table 13: Crisp output for batteries waste sub parameter

Batteries waste						
Cancer	Kidney		…	…	Soil	
6.61	2.39	2.16	…	…	6.62	6.63

Table 14: Crisp output for tube lamp waste sub parameter

Tube lamp waste	
Air	Kidney
6.58	5.17

Table 15: Crisp output for cloth waste sub parameter

Cloth waste
Air
5.17

Table 16: Crisp output for each waste parameter

No	Variable	Co value
1	Plastic waste	3.82
2	Factory water waste	4.35
3	Cloth waste	3.17
4	Batteries waste	5.81
5	Electronic waste	4.73
6	Tube lamp waste	3.32

Table 17: Nomadized SAW value for each waste parameter

No	Variable	Normalized saw
1	Plastic waste	0.657
2	Factory water waste	0.748
3	Cloth waste	0.545
4	Batteries waste	1.000
5	Electronic waste	0.814
6	Tube lamp waste	0.571

Table 18: Final value for each parameter

No	Variable	Final value
1	Plastic waste	1.314
2	Factory water waste	1.497
3	Cloth waste	0.545
4	Batteries waste	2.000
5	Electronic waste	1.628
6	Tube lamp waste	0.571

Conclusion

Factory water waste, plastic waste, batteries waste, cloth waste, and tube light waste are among the six characteristics examined in this study. There are different sub-parameters for each of these parameters. For each waste, these sub-parameters will be utilized as values. Soil, air, water, cancer, leaver, and kidney are the sub-parameters.

The approach's foundations are fuzzy logic and a simple additive weighting mechanism. The model is specified in a class diagram based in an object-oriented manner and the results of these calculations and results are published in the form of a website.

In the built model, there are six different types of garbage. Each trash is assigned a value by a corporate employee based on their experience working in the firm to recycle waste and their educational background. To get the best outcomes, further study is required. You can add numerous characteristics or criteria linked to hazardous waste to acquire the best results in identifying the most hazardousness.

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Author’s Contributions

Timothy Marcelleon: Analyzed all data, designed the model, and finalized the manuscript.

Ditdit Nugeraha Utama: Reviewed and finalized the model and manuscript.

Ethics

This manuscript substance is the authors' own original work and has not been previously published somewhere else. Authors already read and approved the manuscript and no potential ethical issues are immersed.

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