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An Estimation of Jeram Sanitary Landfill Lifespan using Artificial Neural Network (ANN) Modelling Analysis

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ABSTRACT

The ability to forecast the quantity of municipal solid waste (MSW) is critical for long-term coordination of MSW. Forecasting the amount of MSW is often difficult due to the lack of data, and even when data is available, it is frequently inaccurate. Therefore, planning and implementing sustainable solid waste management strategies is important to determine the accuracy of solid waste generation's prediction. With regards to the situation, waste prediction models have been conducted to verify the effectiveness of the models towards the prediction of solid waste generation. As one of the most effective non-linear models, the Artificial neural network (ANN) model has been effectively utilized in the prediction of municipal solid waste at the Jeram Sanitary Landfill in Selangor's state. Datasets of solid waste generation, population, number of trash truck trips, and oil price index were used as input to the model for 114 weeks between 2018 and 2020. The generated models' efficiency was measured using the mean square error (MSE) and coefficient of regression value (R-square). Both measurements showed a good accuracy with the lowest value of MSE at 6379.6, and high value of R-square at 0.91585. Based on the data from 2018 to 2020, The Jeram Sanitary Landfill is expected to last 9.6 years, according to the ANN model. The current study contributes in forecasting and allocating crucial resources that will be necessary in the future for effective solid waste management, as well as exploring alternate approaches to achieving long-term objectives.

Keywords: *Artificial Neural Network, Municipal solid waste, Sanitary Landfill, Forecasting Model, Lifespan Estimation*

1. INTRODUCTION

One of the most effective tools for attaining sustainable development is the environmental management. The transition of economic and technology into a transformation of population lifestyle has led to the increment rate of the Solid Waste Generation (SWG) within the city [1]. The goal of solid waste management is to remove trash from the community as fast as possible by minimising its volume in order to maintain a stable and healthy environment. According to [2], urbanization, economic growth, and an improved standard of living and life expectancy for urban residents had come up with the rising of solid waste disposal. Malaysia's population is rapidly growing, with 32.6 million people expected in 2019. As a result, a massive amount of solid waste has been generated, estimated to be around 38,200 tonnes per day (1.12 kg/cap/day) [1]. In order to address this global issue, landfilling is the most effective approach to settle the collected waste for eventual waste dumping. Landfills are specifically designed places where waste is disposed of in a controlled manner in or onto land but are sources of strong

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contaminants. The goal is to keep waste from coming into contact with the environment, which includes streams and rivers that provide drinkable water to communities. It is essential to track the lifespan of current landfills in order to efficiently manage a limited resource and prepare for its future use. The anticipated solid waste data can be utilised to improve and optimise landfill site operations, estimate the landfill site's future life duration, and optimise alternate disposal options [2].

Most of landfills in Malaysia have experienced an inadequate facility system and proper management. Therefore, this could contribute to the causes of pollution in Malaysia due to the inefficiency of management at the landfill's site. Malaysia's population is rapidly growing, with 32.6 million people expected in 2019. As a result, a massive amount of solid waste was created, estimated to be over 38,200 tons per day. The increment amount of SWG has contributed to the potential threat to society, economy, and environment. The landfill is the place where the final waste disposal, has caused a significant change towards the landfill's environment. Forecasting Municipal Solid Waste (MSW) at landfills, on the other hand, is a difficult undertaking due to a lack of data, discrepancies in the data acquired, and the selection of appropriate forecasting methodologies. Traditional forecasting approaches, such as time series, regression, and input-output methods, are based on semi-empirical mathematical technique that necessitates a large amount of previous data. These approaches, however, are found to be'-xm no longer effective.

Some studies have been carried out with the intent of estimating the lifespan of landfills using various modelling approaches. Recently, various Artificial Intelligence (AI) system have been explored by researchers including support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), and k-nearest neighbours (kNN) [3]. The presence of versatility in AI models, as a deep machine learning as part of computational models has recently gained appeal. According to [3] findings, artificial intelligence models demonstrated excellent prediction performance and might be applied to construct municipal solid waste forecasting models, allowing for the prediction of landfill lifespan. The ANN has the ability to process enormous amounts of data, identify complicated nonlinear correlations between different variables, and detect probable interactions between predictor variables implicitly [4]. The structure and functioning features of human neurons and biological neural networks inspire the concept of ANNs [2]. Moreover, the potential of ANN to learn and apply relationships between data sets while providing accurate and timely estimates has made it increasingly appealing for many engineering fields [4].

Sanitary landfills are the most extensively used solid waste disposal option in the world [1]. The Jeram Sanitary Landfill is located in Mukim Jeram, 20 kilometres northwest of Kuala Lumpur, and is located between the coordinates of 3110 2000 North and 101210 5000 East. The landfill has a total area of 52 hectares, with six trash disposal phases, and was expected to receive about 2,050 tonnes of waste per day during a 10-year period beginning in 2007 [5]. The Jeram Sanitary Landfill site is seen in plan view in Figure 1. The ANN technique was used in this study to create an empirical model to forecast the lifespan of the Jeram Sanitary Landfill. The process of neural network works from the input, where it receives and generates the output. The input layer plays the role to receive data from external neurons. The output layer is used to estimate the outcome of the result, where the problem solution is obtained.

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Figure 1: Plan View of Jeram Sanitary Landfill Site

2. METHODOLOGY

The solid waste management in Malaysia is administered by the Solid Waste Management and Public Cleaning Corporation (SWCorp), which is a collaboration between the Ministry of Housing and Local Government, JPSPN, local governments, and Worldwide Holdings Berhad, as a private concessionaire. The Selangor state government has appointed KDEB Rubbish Management as the private concessionaire to handle waste disposal and public cleanliness starting of November 1, 2018[6]. Jeram Sanitary Landfills in Kuala Selangor are currently managed by Worldwide Holdings Berhad and are dedicated to municipal solid waste (MSW) collected by the municipalities of Kuala Selangor, Klang, and Petaling in the state of Selangor. The existing landfill was built in six phases to accommodate solid waste disposal. Figure 2 depicts the study's methodology, which includes the study region, data collecting, pre-processing data and analysis, ANN model, ANN evaluation, SWG estimation in 2020, and lifespan forecast for the Jeram Sanitary Landfill.

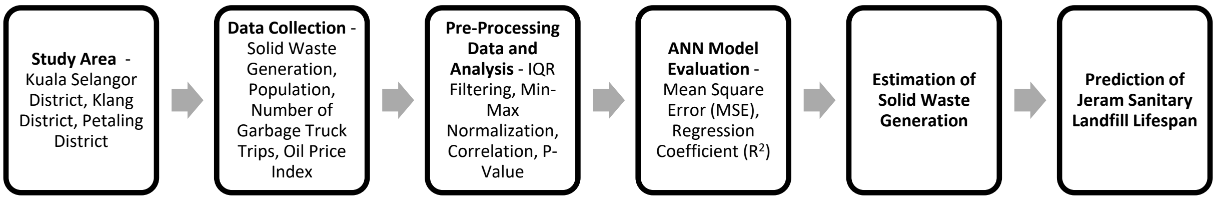

Figure 2: The methodology of the study's process flow

2.2 Secondary Data Collection

Population, data on solid waste , number of garbage truck trips, and oil price info were obtained from the KDEB Waste Management Sdn. Bhd. and Department of Statistics Malaysia. The information was gathered for datasets spanning the years 2018 to 2020. These data are important for future estimation of landfill lifespan in order to prepare for better solid waste management in future. These data are critical for estimating landfill lifespans in the future and planning for better solid waste management.

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The output of MSW has been substantially increased due to rising population levels, expanding economies, fast urbanisation, and rising community living standards[7]. Figure 3 and 4 illustrated secondary data from the SWG's trend and population in Kuala Selangor, Klang, and Petaling districts during a period of 144 weeks from 2018 to 2020.

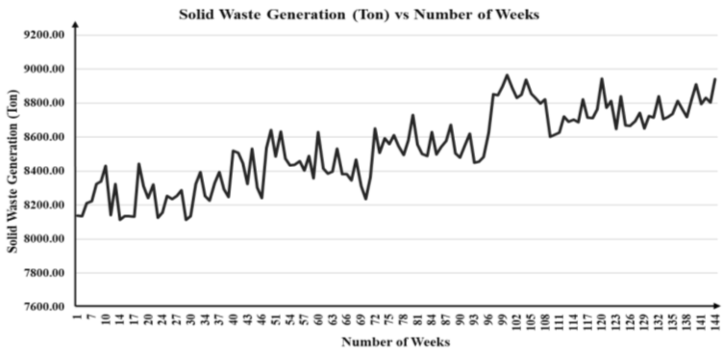

Figure 3: Solid Waste Generations Secondary Data from 2018 to 2020

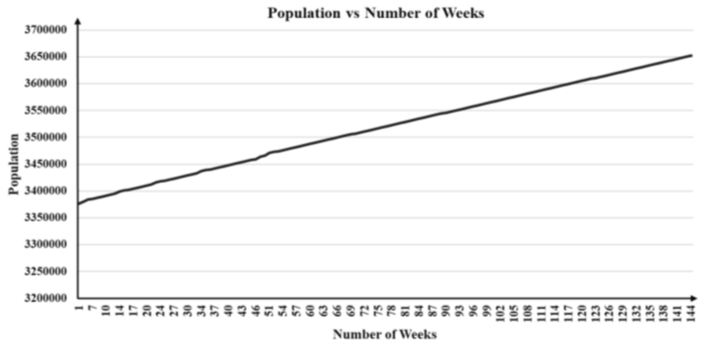

Figure 4: Population Secondary Data from 2018 to 2020

The frequency of garbage truck trips and the oil price index were also factors in predicting the landfill's lifespan. Solid waste transportation required the use of a garbage truck to transport waste from a variety of sites, including business, residential, industrial, and public institutions. As the number of solid waste transportation trips increased, so did the volume of solid trash collected for disposal at the landfill. The number of garbage truck trip’s trend and oil price index’s were illustrated in Figure 5 and 6.

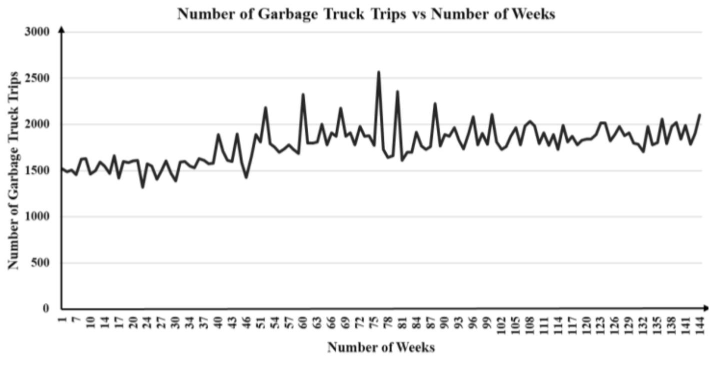

Figure 5: Trips Made by Garbage Trucks from 2018 to 2020

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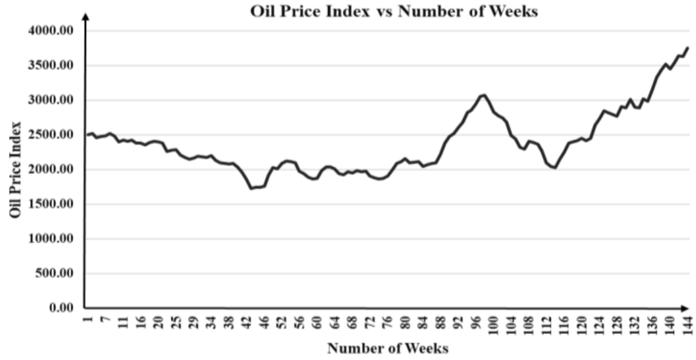

Figure 6: Oil Price Index from 2018 to 2020

2.3 Pre-Processing Data

In order to determine the datasets' reliability, the interquartile range (IQR), min-max normalisation, correlation, and p-value were used to compare the estimated solid waste generation from the ANN analysis to the actual solid waste generation. The IQR displays each dataset's results in order to identify outliers. In order to improve the performance of the results, the datasets were first put through a data filtering process. As a result of the literature research, the Interquartile Range (IQR) was adopted. This procedure must be followed in order to identify the data of the outlier in the secondary data that has been gathered. The IQR value was calculated by using the Equation (1), which involved subtracting the value of the upper limit from the value of the lower limit. The upper and lower limits are shown in the Equation (2) and (3).

$$IQR = Q3 - Q1 \tag{1}$$

$$Upper\ Limit = Q3 + 1.5\, IQR \tag{2}$$

$$\text{Lower Limit} = \text{Q1} - 1.5\ \text{IQR} \tag{3}$$

The datasets were sorted from small to large values to describe Q3, which accounted for 75 percent of the total data, while Q1 is responsible for 25 percent of the datasets. After detecting outliers in the IQR method, the datasets were normalised using min-max normalisation, which translates dataset ranges from 0 to 1. This can be accomplished by using Equation (4), as below.

$$X_{normalization} = (X - X_{min}) / (X_{max} - X_{min}) \tag{4}$$

$X_{normalization}$ was the normalised dataset, with X being the original dataset. Where X_{min} is the original datasets' minimum value and X_{max} is the original datasets' maximum value.

The outcome of the IQR analysis is shown in Table 1. The IQR process must be used to identify the outlier in order to retain the data in a significant outcome for ANN modelling analysis. The datasets in this study preserved 96 percent of the data's originality. On the input and output variables, correlation and p-value analyses were done as tabulated in Table 2. The correlation coefficient and p-value between the dependent and independent variables are represented by these numbers. A correlation value larger than 0.7, according to [8], shows a strong relationship between the dependent and independent variables. Values between 0.5 and 0.7, on the other hand, indicate a moderate relationship. The population achieved the highest correlation

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coefficient of 0.865, with a p-value less than 0.05 level of significance, according to the correlation coefficients in Table 2. As a result, it is worth noting that the population has a considerable impact on solid waste output.

Table 1: Data Pre-processing for IQR

Datasets	1st Quartile	3rd Quartile	IQR	Upper Bound	Lower Bound	Outlier
SWG	8324.79	8713.09	388.30	9295.54	7742.34	Negative
Population	3441919.50	3582161.00	140241.50	3792523	3231557	Negative
Number of Garbage Truck Trips	1609.75	1892.00	282.25	2315.38	1186.38	Positive
Oil Price Index	2049.81	2522.04	472.23	3230.39	1341.46	Positive

Table 2: Data Pre-processing for IQR

Dependent Variable	Independent Variable	P – Value	Pearson Correlation	Type of Correlation
Solid Waste Generation	Population	2.47E-44	0.87	Strong Positive
	Number of Garbage Truck Trips	1.99E-20	0.67	Moderate Positive
	Oil Price Index	8.47E-10	0.50	Moderate Positive

2.4 Artificial Neural Network (ANN)

The brain's immensely complicated network of interconnected neurons is simplified using artificial neural networks (ANNs). Layers of neurons, which are the individual processing units, compose the framework of a feed-forward multilayer ANN. They receive input, process it, and pass it forward to the next layer [9] . The bias and weights were created using the MATLAB ANN tool, which prepares the model for forecasting. Figure 7 depicts an ANN architecture model with three inputs, one hidden layer with three neurons, and one output.

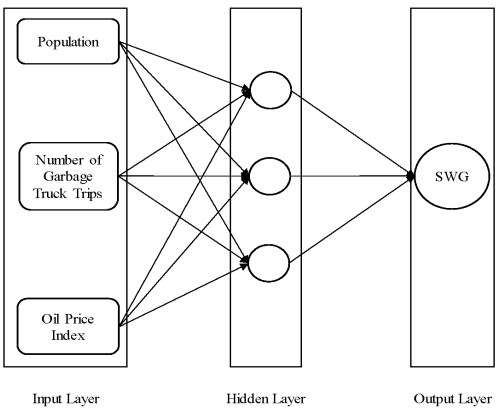

Figure 7: ANN Structure Model

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According to the findings tabulated in Table 3, three neurons with a single hidden layer were sufficient in this model. The 3-3-1 model seemed to have the highest coefficient regression and produced the most precise accuracy, with R-square values of 0.90980 for training, 0.93819 for testing, 0.91939 for validation, and 0.91585 for overall.

Table 3: Artificial Neural Network (ANN) Analysis

ANN Model Structure	No. of Neuron	Epoch	MSE	Regression			
				Training	Testing	Validation	All
3-1-1	1	244	9102.13	0.74650	0.82447	0.74236	0.75888
3-2-1	2	128	11203.36	0.86747	0.92418	0.93644	0.88487
3-3-1	**3**	**1000**	**6379.60**	**0.90980**	**0.93819**	**0.91939**	**0.91585**
3-4-1	4	1096	46533.71	0.81842	0.85434	0.83055	0.82601
3-5-1	5	1011	9664.60	0.90253	0.91869	0.91296	0.90434
3-6-1	6	1008	47510.95	0.82434	0.74375	0.75316	0.79482
3-7-1	7	1000	32001.29	0.78536	0.82938	0.73800	0.78697
3-8-1	8	1015	40419.87	0.83638	0.75290	0.81590	0.81851
3-9-1	9	1004	15630.71	0.93950	0.84539	0.84528	0.90562
3-10-1	10	1000	35228.16	0.71241	0.87184	0.83990	0.75749
3-11-1	11	1020	33779.32	0.86941	0.48889	0.80722	0.79671
3-12-1	12	1010	29897.99	0.80710	0.80325	0.84818	0.80617
3-13-1	13	1426	8490.50	0.90501	0.84715	0.93213	0.90141
3-14-1	14	1004	11841.38	0.89621	0.90082	0.88494	0.88930
3-15-1	15	1003	9933.42	0.87594	0.73965	0.89908	0.85904
3-16-1	16	1008	41780.33	0.81581	0.77286	0.79411	0.79474
3-17-1	17	1012	29246.15	0.82553	0.52494	0.77870	0.77022
3-18-1	18	1004	13249.25	0.87239	0.81955	0.88388	0.86832
3-19-1	19	1007	27156.10	0.81873	0.63411	0.83191	0.79434
3-20-1	20	1135	21962.30	0.82969	0.31032	0.73932	0.71442
3-21-1	21	1016	16966.31	0.86631	0.71440	0.80682	0.89745
3-22-1	22	1026	32264.41	0.84502	0.63259	0.86380	0.81244
3-23-1	23	1007	67884.45	0.83546	0.78153	0.82012	0.81570
3-24-1	24	1010	27936.65	0.84274	0.78931	0.84535	0.83340
3-25-1	25	1019	27842.08	0.85571	0.80122	0.78214	0.82458
3-26-1	26	1035	35678.46	0.85293	0.77483	0.68078	0.82116
3-27-1	27	1005	35137.99	0.83852	0.65069	0.85714	0.81403
3-28-1	28	1014	22680.86	0.85644	0.76962	0.83162	0.83713
3-29-1	29	1634	30674.40	0.86761	0.50674	0.72977	0.79774
3-30-1	30	1007	37295.78	0.83447	0.84607	0.85595	0.83705

Mean Square Error is a metric used to manage and improve the performance of Artificial Neural Network models [10]. From Table 3 and Figure 8, the lowest value of Mean Square Error (MSE) was of 6379.60. The rest of the ANN models performed well, with the R-square achieve more than 0.7. By carrying out the analysis in the MATLAB (R2018a 9.4) programme, the outcomes of the ANN's model produced a reliable result that delivers the lowest MSE and highest R-square among the others ANN's model. According to [11], over 30 trials with dataset inputs were conducted to examine model reliability and identify the instance with the highest R-square and lowest MSE.

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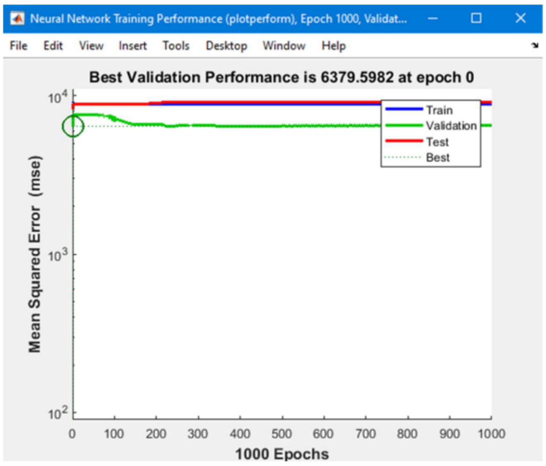

Figure 8: Mean Square Error (MSE) of ANN Model Results

3. RESULTS AND DISCUSSION

3.1 Solid Waste Generation (SWG) Estimation

The accurate forecasting of municipal solid waste quantities is critical for the effective planning of an efficient waste management system and, as a result, the landfill's lifespan. The development of integrated waste management infrastructures, as well as their continuing sustainable development and optimization, is based on projected forecasts of municipal SWG. The study's objective of estimating the lifespan of the Jeram Sanitary Landfill necessitates evaluating the SWG first. Figure 9 displays the actual and estimated data for the year 2020, which are 8941.54 tonnes and 8787.40 tonnes, respectively. The forecasts show a nearly identical result between these two sets of data, previously confirmed by the regression analysis results. As a result, the outcome of the ANN modelling analysis has provided an accurate estimate of SWG.

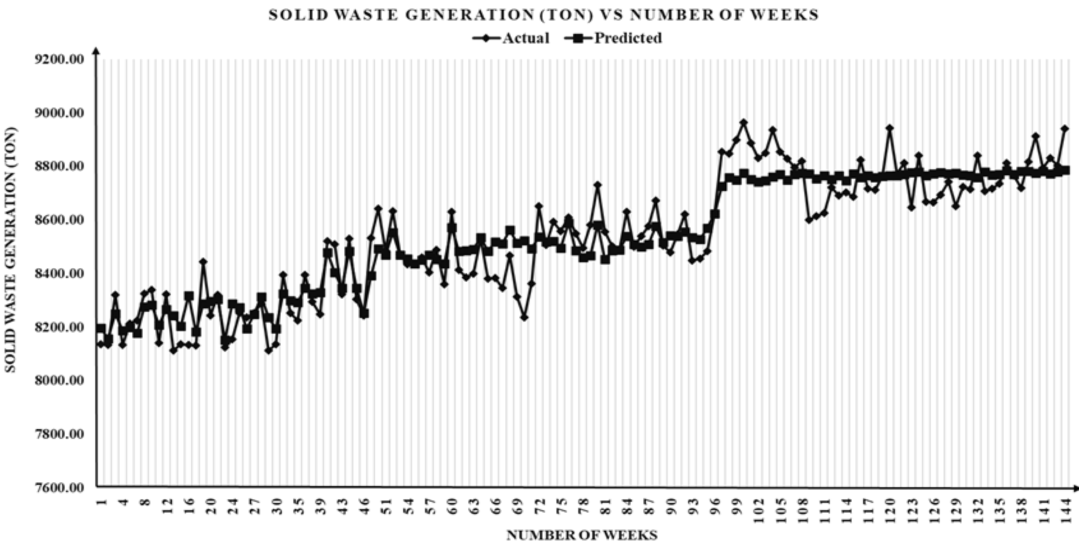

Figure 9: Actual Data and Estimated Result of SWG

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The inconsistency of actual solid waste generation has made it difficult for ANN's model's anticipated result to match the actual figure. The structure of the ANN is significant in ANN modelling, according to [12], because it affects the forecasting procedures. The results of the estimated SWG will differ depending on the ANN model used. According to prior study, the type of input employed as a variable in AI model applications affects the variation trends of predicted SWG [3].

3.2 Lifespan Prediction of Jeram Sanitary Landfill

Increasing MSW generation in Kuala Selangor, Klang, and Petaling District will undoubtedly lead to a considerable reduction in the life span of the Jeram Sanitary Landfill. The Equation (5) below, was used to plan the landfill's lifespan.

Landfill Lifespan = Volume of SWG in the end of 2020 + Soil Cover (Ton) x 0.85 (5)
by 2020

The actual data obtained from Malaysia's Department of Environment and forecasted data from this study of SWG in 2020 was shown in Table 3. The predicted outcome indicated that approximately 9.4 years of landfill's lifespan were required to accumulate the 8787.40 tonne of solid waste generated in 2020, compared to data obtained from Malaysia's Department of Environment. This demonstrates that there is just a 2 percent discrepancy between the two sets of data.

Table 3: Artificial Neural Network (ANN) Analysis

	Actual Data of Solid Waste Generation	Estimation of Solid Waste Generation
Volume of SWG in the end of 2020 (Tonnes)	8941.54	8787.40
Landfill's Lifespan in the end of 2020 (Year)	9.6	9.4

4. CONCLUSION

It is critical to track the lifespan of existing landfills in order to properly manage a limited resource and prepare for future use. The proper input variables must be chosen in order to simulate a reasonably acceptable model. The results show that three input variables are suitable for predicting the SWG of Klang District and Jeram Sanitary Landfill's lifespan. Figures indicate a nearly identical relationship between estimated and actual values, which is supported by the regression analysis results. Derived from the three input variables (population, number of garbage truck trips and oil price index), the model predicted that the landfill's lifespan at the end of 2020 would then have decreased by 2 percent. Other input variables should be used in future studies to improve the results of the utilised model.

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