# Developing a Hybrid Regression-Metaheuristic Forecasting Model for University Solid Waste Generation

Pongchanun Luangpaiboon and Lakkana Ruekkasaem*

***Abstract*—The purpose of this study is to investigate and compare forecasting trends of university solid waste (USW) at a private university in Bangkok using a combination of statistical and metaheuristic algorithms. The university's municipality solid waste data was prepared, collected, and converted so that it could be processed by a decision support system. Historical data is available for 16 years beginning with fiscal year 2005. Factors influencing USW quantities include the number of students, staffs, and others. USW is divided into two data sets: learning data sets and test data sets. The first will be examined using multiple regression and metaheuristics components. The learning datasets differ in data density because factor data is collected on an annual basis. As for the USW data, the data is recorded through the decision support system on a monthly basis. The second will be combined with the proposed method to determine the trend in substituting the prediction equation for USW management. The primary goal of this paper is to develop an effective USW forecasting model to deal with this problem by combining regression and metaheuristic techniques. Based on an empirical analysis of the indicators' annual data and the USW's monthly data from 2005 to 2020, we find that the hybrid method based on the linear equation performs well for all performance measures of the mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean square error (MSE). These findings may be useful in the preparation, configuration, and implementation of a waste management system at a university.**

***Index Terms*—Multiple regression, linear and quadratic equations, metaheuristics, differential evolution**

## I. Introduction

The development trends that many rapidly growing urban societies including the universities face, it is extremely difficult to process decision-making aids for proper operation. Forecasting the occurrence of solid waste on campus is critical to solid waste management [1]. Through higher predicted prediction accuracy, this could result in more appropriate guidance. The generation of interactive solid waste will be influenced by population growth, infrastructure development, changes in unit size, employment, and the impact of waste recycling. Reliable models for predicting the overall impact of students, staffs, and others have been developed. These will help with solid waste management practices [2].

Forecasting techniques include data mining [3], time series analysis [4], an adaptive network-based fuzzy inference system (ANFIS) [5], regression [6], neural network analysis [7], and metaheuristics [8]. In the past, researchers have found it extremely interesting to improve forecast accuracy using a variety of methods. The multiple regression (MR) model is well-known for calculating the generation rates of municipal solid wastes. MR models have been widely used in a variety of scientific fields due to their versatility and well-founded theory. The main disadvantage is the database preparation.

The hypothesis on both the overall model and individual coefficient tests for using MR in this study is based on the effect of the indicators or parameters on the response or USW generation. To improve approximations, methods for allowing regression models to measure curvilinear associations as well as non-additivity have been developed. Nonlinear prediction models can be used in these cases, but they increase the modeling process's complexity. An experienced user understands how to incorporate curvilinear characteristics into a regression model when using multiple regression.

Since the first set of algorithms, there have been numerous studies in metaheuristics for global optimization problems [9]. Genetic, particle swarm optimization, ant colony optimization, simulated annealing, and taboo search algorithms are examples of classic metaheuristics. Later, there is an exponential increase in the number of new algorithm offerings. Metaheuristic algorithms are currently judged not only on performance, but also on the novelty of the simulation process through a specific area.

The primary goal of this study is to prepare for the development of a USW generation forecasting system for each department via a university network with varying dataset density. It is proposed to use a hybrid regression-metaheuristic method (HRM). The remainder of the paper is structured as follows. The following section explains university solid waste management and relevant related methods, which is followed by section IV, which is the proposed hybrid regression-metaheuristic or HRM method. Sections V and VI contain numerical results as well as a conclusion.

## II. University's Solid Waste Management

In the University's Solid Waste Management system, data is collected from relevant departments and interviews with responsible university staff during waste collection, removal/transportation, and disposal both inside and outside the building, waste sorting, and projects or activities that support such operations. It was discovered that the amount of solid waste generated throughout the university, as well as the rate of solid waste generation (kg/person/day), has steadily increased since 2005, when all relevant information

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management systems were installed.

Simultaneously, the amount of solid waste that has been properly disposed of according to academic principles and recycled for use is likely to increase, but only marginally in comparison to the growing volume of solid waste. As a result, one of the most pressing environmental issues is the solid waste crisis. Because of the increasing severity of the problem in terms of the increasing amount of solid waste, the best solid waste disposal sites are becoming increasingly scarce. It was incorrectly implemented and has not been updated.

The accurate study of solid waste trends is therefore critical to solid waste management. That is, it can be used to make decisions when planning and designing a solid waste management system, such as determining the size and number of garbage bins, garbage trucks, and the size of the waste disposal area. It can be used to provide budget allocation for various activities in order to make university personnel understand the importance of waste reduction. As a result, it is necessary for all relevant departments to estimate the amount of solid waste in the responsible area for decision-making in planning the design of the university's overall waste management system. The university population consists of students, staffs, and others such as shop operators who are stationed there. Physical Development Center is an official unit in charge of the university's solid waste management. USW types and sources can be shown in Table I. Fig. 1 demonstrate various sources of USW.

TABLE I: UNIVERSITY SOLID WASTE TYPE AND SOURCES [10]

| Type | Sources |
|---|---|
| Papers | Paper scraps, cardboard, newspapers, magazines, bags, boxes, wrapping paper, shredded paper, and paper beverage cups. |
| Plastics | Bags, Bottles, packaging, containers, lids, cups |
| Glass | Bottles, Incandescent and fluorescent bulbs, broken glassware, colored glass |
| Metal | Textiles, leather, rubber, multi-laminates, e-waste, appliances, ash, other materials |
| Organics | Food scraps, yard (leaves, grass, brush) waste, wood, process residues |
| Others | Textiles, leather, rubber, multi-laminates, e-waste, appliances, ash, other materials |

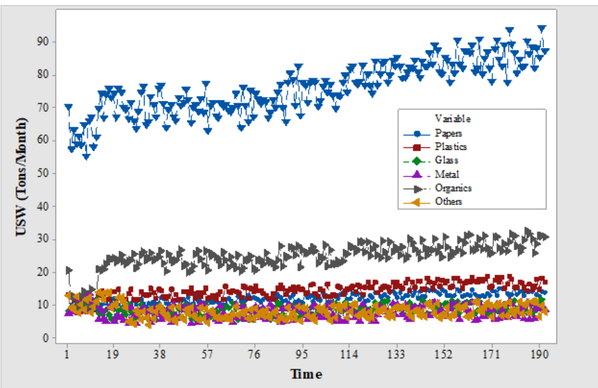


Fig. 1. USW amount with different types.

## III. RELATED METHODS

### A. Multiple Regression

Multiple regression is a numerical evaluation that illustrates the association between the variables or indicators (X) that influence with over one independent variable or response (Y). The goal of multiple regression analysis is to quantify the strength of the relationship between two or more factors and to predict the value of Y based on the value of X [11]. The strength of relationships between factors and their predicted response value can be determined via correlation coefficient. Furthermore, when using multiple regression testing, the coefficient of determination can be used to determine how much of the total variation in the response Y can be accounted for by dependents (X). To recheck the strength of the regression model, partial and multiple regression tests can be used. The t test is used to test each factor partially, and the f test multiple regression is used to determine whether a group of factors has an effect on responses at the same time. Finally, in order to compare the optimal performance of a model prediction, mean absolute deviation (MAD), mean square error (MSE), and mean absolute percentage error (MAPE) can be calculated.

### B. Differential Evolution Algorithm

Differential evolution (DE) is a population-based metaheuristic algorithm that optimizes a problem by iteratively strengthening a candidate solution according to the evolutionary process [12–13]. Under few or no optimization problem assumptions the DE can rapidly investigate very large domain spaces at solving complex problems in many scientific and engineering fields. The algorithm locates the design area by preserving the population of alternative solutions (individuals) and generates new solutions by combining existing solutions using specific processes [14]. The best candidates are maintained in the next iteration of the algorithm, so that the individual's new objective values are updated as part of the population [15]. Otherwise, the new objective value will be overwritten. The process will be repeated until an acceptable termination threshold is reached.

### C. Experimental Designed Plan

Design and analysis of experiments (DOE) are powerful procedures for improving both products and processes. When considering the numerous factors influencing experimental results, this can reduce the number of required experiments from the standpoint of design fields. It is a method for determining the relationship between factors influencing a process and the process's output. To put it another way, it is used to discover cause-and-effect relationships. This information is required to handle process inputs and optimize output. DOE can demonstrate how to conduct as few experiments as possible while retaining the most critical information.

## IV. HYBRID REGRESSION-METAHEURISTIC METHOD (HRM)

The sequence of monthly USW generation is the main time series in this article, as stated in the university fiscal year reports from 2005 to 2020. The dataset includes USW generation as well as selected indicators. The selection of indicators, as discussed in the previous section, is intended to improve USW generation forecasting. We conclude that influential indicators must be chosen carefully in order to reveal a significant relationship between USW generation and indicators.

The properties taken into account for indicator selection are discussed in this article such as students, staffs, and others. However, the annual report of these three sources or indicators of USW has been recorded. To make effective use of multiple regression, you must first understand the regression model. The fundamental regression model is linear. However, linear equations have a number of limitations. For example, if only linear methods and linear models are used, some potentially useful relationships may be overlooked. Following consideration of these issues, the USW generation forecasting based on three indicators was modeled in this study using various forms.

The more reasonable approximation is a hybrid model integrating DE for an estimation of USW generation in linear or quadratic form. Given that the undertaking is to minimize a function with five decision variables, each DE stage of DE can be described in detail [16–18]. The DE algorithm's entire process is repeated for the specified number of generations [19]. In simple DE, an initial population of A individuals is generated at random from a uniform distribution within lower and upper boundaries. Individuals evolve through crossover and mutation to produce a trial vector. The trial vector competes with his parent to choose the best fit for the next generation. DE procedures are as follows:

*Initialization*: The search process begins in this step by generating a random C number of parameter vectors. C does not change during the optimization process in this case.

*Mutation*: In this step, a vector from the current population (or parent) is chosen as the target vector. The terms "parent" and "target vector" are used commonly associated [20].

*Crossover*: This step involves exchanging components of the target vector and mutant vector in order to diversify the current population. A new vector is created and named trial vector. The trial vector is also referred to as the offspring. There are two types of crossover available: binomial crossover and exponential crossover [21].

The candidates with the finest values are kept in the next algorithm iteration in such a way that an individual's new objective value is enhanced and thus becomes fraction of the population; otherwise, the new activation value is abandoned. The procedure is iterated until a designated termination criterion is met. The flowchart of the DE algorithm is described in Fig. 2.

The fundamental DE has five primary controllable parameters: crossover (A), mutation factor (B), population size (C), random seed (D), and maximum number of functions evaluations (E). These parameters are essential in enhancing the achievement of the DE's search process. For fine-tuning DE parameters, the dual response surface method is introduced.

The response surface methodology (RSM) is a class of computational techniques for designing and implementing process or product development outcomes [22, 23]. On surface characteristics or contour diagrams, the relationship of various factors that affect the response aims to forecast the optimal level of factors [24, 25]. RSM techniques used today have proven to be more useful and convenient. The essence of this technique is that the number of experimental sets is small, and the RSM equations will improve our understanding of independent variable interactions [26]. This is useful in determining the best level for the experiments.

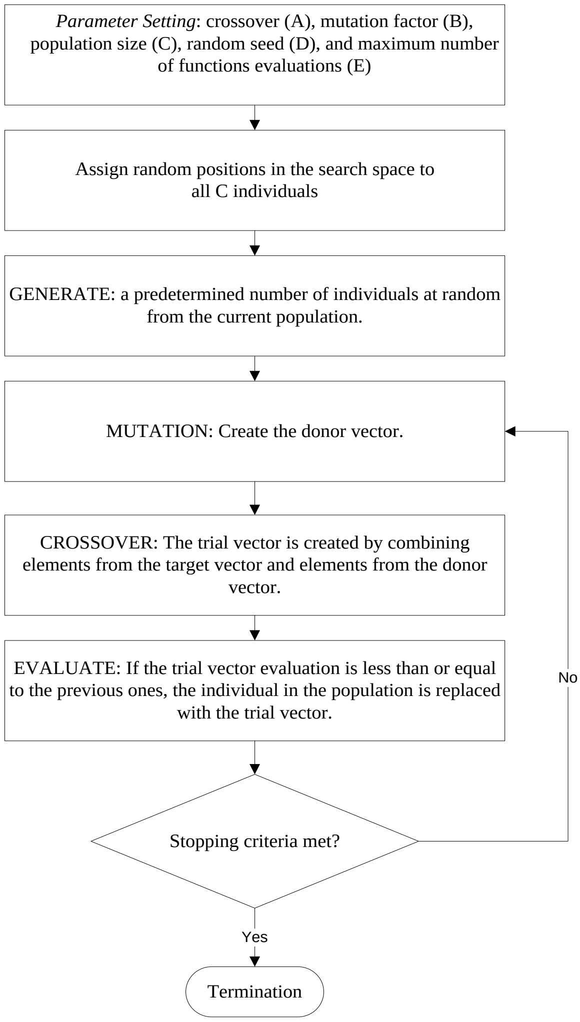


Fig. 2. Flowchart of the DE.

The Copeland and Nelson's dual response surface method is used to determine the parameter levels of the DE algorithm method by minimizing the mean square error (MSE). Fitted equations in a linear or quadratic model between factors A, B, C, D, and E can be formed by designing two-level experiments. The equations can also be analyzed for high reliability, which includes testing the equation's suitability with various parameters to demonstrate that the equation is suitable and that the accuracy of calculating the response value is close to the true value.

The CN method's brief procedure is to determine the controllable parameters, including the response, using a two-level experimental design. The process of improving and developing a model is carried out in order to estimate the response variable's mean ($\hat{y}_{\mu}$) and standard deviation ($\hat{y}_{\sigma}$). The appropriate parameter value can be determined by adjusting the mean and standard deviation using the following mathematical model.

$$\min \ \hat{y}_{\sigma}$$
$$\text{subject to } (T-\Delta) \leq \hat{y}_{\mu} \leq (T+\Delta);$$
where
$$\hat{y}_{\mu} = a_0 + \sum_{i=1}^{k} a_i x_i + \sum_{i=1}^{k} a_{ii} x_i^2 + \sum \sum_{i<j}^{k} a_{ij} x_i x_j;$$
$$\hat{y}_{\sigma} = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum \sum_{i<j}^{k} b_{ij} x_i x_j;$$

and $\Delta$ is the maximum allowable deviation from the estimated mean ($\hat{y}_{\mu}$) from the specified target value. Fig. 3 depicts the sequential procedures of the HRM based on the DE.

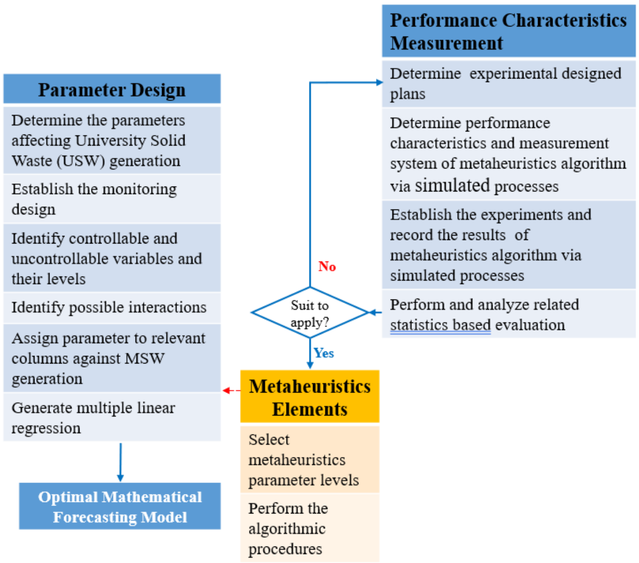


Fig. 3. Procedures of the HRM.

## V. Numerical Results

Based on previous research on USW generation, we propose forecasting methods that can account for all of the effects presented for better prediction. This study introduces a hybrid regression-metaheuristic method, which is a more traditional method of forecasting with robust and superior performance when metaheuristic features are used. The model can accommodate indicators or independent variables. The proposed methods are created by combining existing regression-based forecasting methods that are classified based on their specialties. The existing metaheuristic algorithms are then proposed to generate alternative coefficients in the following step. The differential evolution algorithm was chosen for this study.

DE, despite its simplicity, outperformed at solving complex optimization problems. The three main controllable parameters in DE are crossover (A), mutation factor (B), population size (C), random seed (D), and maximum number of functions evaluations (E). Because the values of these parameters have a meaningful effect on the DE performance, adjusting those control parameters can be difficult. DE excels at exploring the solution space. This is the primary benefit, but the obvious disadvantage is the low efficiency of the exploitation process. This could lead to disruption and/or premature convergence.

The experiment must be carefully carried out in the early stages of using metaheuristic algorithms to obtain the best parameter levels before proceeding to analyze it. Prior to the experiment, a brainstorming session was held as part of the process of designing the most efficient and appropriate experiments. It was used to establish the experiment's parameters, response, and strategy. At almost the same time, it guarantees that the experiment meets the objective and the practitioner's needs. It means that an appropriate and correct strategy is required to conduct a successful experiment. With the assistance of a subject matter expert, a two-level experiment design was carried out.

To investigate the optimal level of DE parameters, the data is simulated and analyzed using various mathematical equations, including the response surface equation, which has only one optimal solution [27]. The optimal solution to the response surface equation is near the edge value. as well as response surface equations with multiple best solutions. Through interaction effects, the Analysis of Variance (ANOVA) can determine the parameters that influence both the mean and variance responses (Fig. 4). The appropriate parameter level for each type of response surface equation was then determined using multiple regression analyses [22]. Using the Copeland & Nelson method, the optimal degree for parameters influencing the dual response was determined by analyzing multiple regression equations of mean and variance, with the mean target value set to −3.6 and "Δ" = 0.05 as followed. The preferred DE parameter settings for A, B, C, D, and E is 0.0001, 0.05, 20, 0, and 30, respectively, based on all response surfaces.

$$\text{Min} \quad \hat{y}_{\sigma} = (0.00058 + 0.000154\,D + 0.000059\,E)^{0.5}$$

Subject to

$$-3.65 \le 3.6288 - 16A + 0.765B \le -3.55$$
$$0.0001 \le A \le 0.001$$
$$0.05 \le B \le 0.075$$
$$15 \le C \le 20$$
$$0 \le D \le 2$$
$$20 \le E \le 30$$

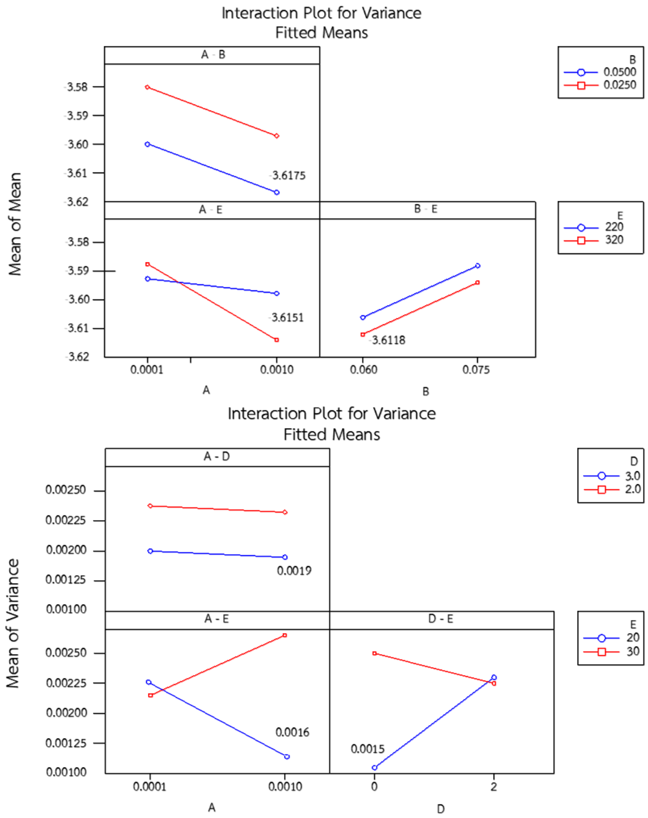


Fig. 4. Interaction effects plot based on the mean and variance, respectively [28].

Various sources of USW (Fig. 1) should be considered to provide a better comparison of 'forecasts' to 'actuals.' Fig. 4 shows how the model developed using historical data up to 2020, as well as the model developed monthly, were both applied to predictor variables recorded between 2005 and

2020 to generate predicted values for USW generation based on three indicators of students, staffs, and others for these years. Setting the optimal DE parameters is also critical. The values of parameters are set based on extensive research to determine appropriate values. As a result, these fixed values are also employed in this forecasting study. For USW generation forecasting, the following linear and quadratic equations are obtained [29]. The obtained coefficients ($\alpha_i$) in both forms are shown in the table below.

TABLE II: COMPARISONS OF COEFFICIENTS AND ALL PERFORMANCE MEASURES IN LINEAR AND QUADRATIC FORMS

| Effect | $\alpha_i$ | Linear | Quadratic |
|---|---|---|---|
| Constant | $\alpha_0$ | 113.6 | -313 |
| Main | $\alpha_1$ | 0.007711 | - 0.031 |
| | $\alpha_2$ | 0.0789 | 0.55 |
| | $\alpha_3$ | 0.3907 | 0.390 |
| Pure | $\alpha_{11}$ | Na | - 0.000001 |
| | $\alpha_{22}$ | Na | - 0.00023 |
| | $\alpha_{33}$ | Na | 0 |
| Interaction | $\alpha_{12}$ | Na | 0.000028 |
| | $\alpha_{13}$ | Na | 0 |
| | $\alpha_{23}$ | Na | 0 |
| MAPE | | 4.07071059 | 4.0707269 |
| MAD | | 3.03864182 | 3.03787692 |
| MSE | | 13.6617616 | 13.642086 |

Data from 2005 to 2020 are used to validate the models. Table II displays the mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean square error (MSE) between estimated and observed data. According to Table II, the proposed HRM approach for forecasting USW generation in the university is successful and robust. Because of the fluctuations in the indicators, the linear form provides a better-fit forecast than the quadratic form.

The collected data will be used in a comparative study of the two forecasting equations using the HRM method in 2021. The actual waste volume was 1016.39 tons per year, and the HRM method predicted USW generation at 996.76 and 990.20 tons per year, respectively, in linear and quadratic forms. When using the linear form, the MAPE, MAD, and MSE performance measures were 2.58, 19.63, and 385.35, respectively. When using the quadratic form, the MAPE, MAD, and MSE increase to 4.29, 44.34, and 1965.86, respectively.

A model is used to forecast future indicator levels based on previously observed values from annual university reports. Figs. 5–7 show a simple way to examine the estimated number of all three indicators for the years 2022 and 2023 for the number of students, staff, and others.

In 2022, the forecasted values for three indicators of students, staff, and others are 9750, 1897, and 126. In 2023, the projected values for students, employees, and other indicators are 9982, 1906, and 127, respectively. Using (linear, quadratic) equations, the estimated levels of USW in 2022 and 2023 are (1060.73, 1060.01) and (1077.69, 1077.65) tons per year, respectively.

As shown in Fig. 8, the university generates approximately 14.58 tons of waste per year, which can be classified into five types of waste: papers, plastics, glass, metal, organics, and others, with 32.60 percent organic waste, 19.09 percent plastics, papers 15.82 percent, glass 11.31 percent, metal 10.36 percent, and other waste 10.81 percent.

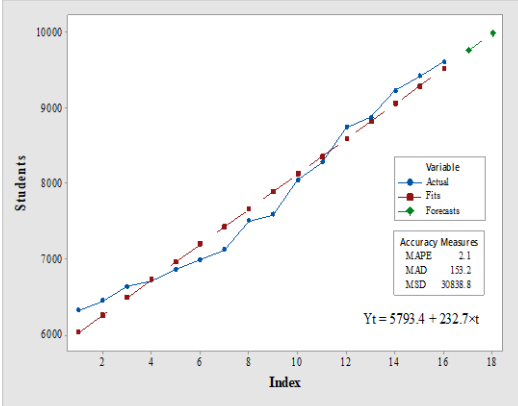


Fig. 5. Actual and forecasted number of students: Building and Premises Division Department (2005–2020).

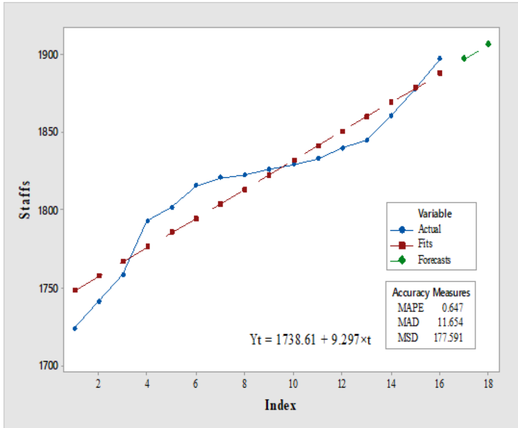


Fig. 6. Actual and forecasted number of staffs: Building and Premises Division Department (2005–2020).

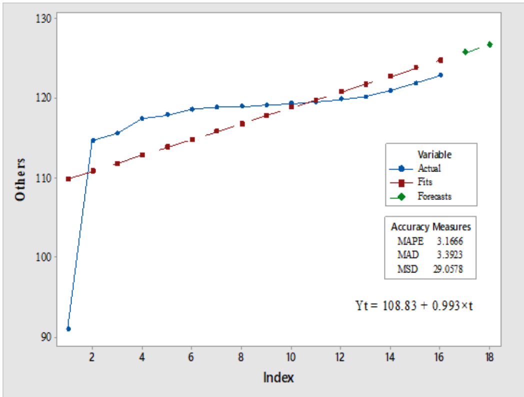


Fig. 7. Actual and forecasted number of others: Building and Premises Division Department (2005–2020).

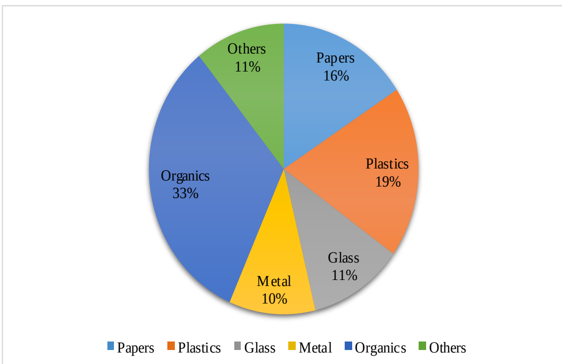


Fig. 8. Types of waste in the university: Building and Premises Division Department (2005–2020).

Waste management is currently handled by the university, which organizes collection and separates all waste. General waste will be disposed of by the Sub-District Administrative Organization, while recycled waste will be managed through a bank project. Organic waste and recycled waste are sold to the private sector. Organic waste, such as leaves and branches, was used to create fertilizer. Recirculated for university gardening, but more than enough given the number of leaves/branches left behind in various locations across campus.

## VI. Conclusion

The goal of this study is to develop guidelines for the management of the university's solid waste, as well as future waste management planning. This waste management system will be used as part of an approach to improving the system to aid in the management of solid waste disposal. This could raise awareness about the amount of waste generated, the different types of waste, including various components, modes of transportation, and garbage collection within the university.

The hybrid regression-metaheuristic forecasting model is used to estimate trends in university solid waste (USW). In this case study, relevant data from all sources of waste generation, such as the number of waste disposal facilities and the target number of people in each facility, are gathered. Data screening, visualization, and display were summarized in order to create forecast prototypes and further process waste quantity forecasting trends using DE metaheuristic elements.

Each indicator's or independent variable's effect is additive, which is a fundamental assumption in the regression model. Nobody believes the connection is additive any longer. Rather, they believe that this model is a reasonable first approximation to the true model. Consider this analytical approach to be a series augmentation of the goodness of fit test to strengthen the approximation. This attraction to series expansion, however, frequently ignores the neighboring assumption.

With the proposed techniques, the overall USW were estimated in the area of university municipality. According to the numerical results, the amount of waste produced by the 12,015 population in 2022 is 2.75 tons per day, approximately. The average amount of solid waste produced per person per day is 0.23 kg. For the university's solid waste management system, organics, plastic bags or plastics, paper, glass, metal, and others were ranked in solid waste compositions.

As a result, effective waste management, which is the use of technology to convert waste into energy and waste management technology to zero, etc., as a guideline for waste management in universities. This could be used as a waste management model in support of the ASEAN Economic Community, as well as to make the waste management project feasible or the most projects or the least investment risks. As a result, the Private Investment in Government Affairs Act has been used as a supporting factor in the investigation of the university's waste management strategy. The purpose of the Act on Private Sector Participation in State Projects is to provide infrastructure or public services to the state when the state is unable to meet the needs of the people. Quick action efficiency and making the best use of federal resources.

However, latent population studies may be required in the future to successfully complete the research. As an open university, there are many latent populations and forms, such as parents sending their children to the dormitory, relatives visiting patients at medical centers, athletes from various institutions coming to practice and collect, and so on. From the start, the latent population plays a crucial role in accelerating the amount of waste. However, the producer failed to account for the latent population in various calculations, resulting in a difference between the waste generation rate and the actual value. More research should be conducted to investigate the distinctions between discrete and combined bins, as well as the discrepancies in quantity, composition, and density between combined and classified bins.

## Conflict of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Author Contributions

P. Luangpaiboon contributed to the design, conceptualization, methodology, software, validation, visualization of the research, to the analysis of the results and to the writing - review & editing of the manuscript. L. Ruekkasaem contributed to an implementation, formal analysis, investigation, data curation of the research, and to the writing - review & editing of the manuscript. P. Luangpaiboon and L. Ruekkasaem had approved the final version.

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