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Integration of Fuzzy 0/1 Knapsack Dynamic Programming and PROMETHEE Method for Vehicle Exhaust Emission Parametric Optimization and Selection in The Packing Industry

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ABSTRACT

Packaging industries fabricate and transport products in wrapped, sealed, and cushioned containers and boxes on roads, often through fossil-fuelled vehicles that emit carbons. Thus, decarbonization and net zero emission drive are compelling for these vehicles. This paper proposes a robust green logistics interaction model for monitoring and reducing exhaust pipe emissions in an uncertain environment. It uses a hybrid method known as fuzzy-0/1-KDP-PROMETHEE (Fuzzy-0/1 Knapsack dynamic programming-Preference Ranking Organization Method for Enrichment Evaluation) approach to concurrently reduce uncertainty, optimize the capacity of the knapsack and establish the preferred option among the parameters of green logistic. Both PROMETHEE I and II were introduced and tested using logistics data from an Indian environment based on secondary data. The method works by first reducing the effect of uncertainty on the model outcomes. This was achieved by establishing the output space as the fuzzy state, creating fuzzy rules, and mapping degrees to rules. Then, the degrees are used to maximize, ensuring that the weighted sum is not greater than the capacity of the Knapsack. The outcome is then regarded as the element of the green logistics exhaust emission process. The results obtained from the analysis, using the replacement of fuzzy expert (triangular) with fuzzy extent (trapezoidal), fuzzy geometric mean (triangular), and fuzzy geometric mean (trapezoidal) reveal that the fuzzy -0/1-KDP-PROMETHEE method adequately represents the score obtained using the data set from the exhaust emissions.

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1. INTRODUCTION

In the green logistics arena, there is a high proliferation of alternative parameters responsible for vehicle exhaust emissions in the packing industry. Besides, funds to actualize budgets in reducing or eliminating penalties to vehicles, through environmentally conscious vehicle logistics, are becoming more difficult to obtain. However, in the selection and optimization of vehicle exhaust emission parameters, the aim is to obtain useful and accurate results for decision-making. This is achieved when proper randomization is achieved, where the chosen parameters are representatives of the population. Consequently, parametric selection and optimization are increasingly becoming subjects of investigation among researchers. For instance, using simulation, Sarkan et al. (2022) studied the emissions produced by road transport. The parameters studied include the quantity of fuel mixture (i.e. the addition of air to fuel) with analysis on nitrogen oxides (NOx), carbon monoxide (CO), hydrocarbon (HC), and carbon dioxide (CO2). It was concluded that the volume concentration produced is a function of the parameters for the control unit for the engine.

Zhao et al. (2019) examined the vehicle exhaust emission using a car-following model. The emission types are nitride oxide (NOx), hydrocarbon (HC), carbon dioxide (CO2) and carbon monoxide (CO). The utility of the method in controlling and managing signalized intersections was affirmed. Xue et al. (2013) proposed an approach to integrate vehicle exhaust emission and traffic flow for an interaction study. The principal indices of the following gases were considered - nitrogen oxides (NOx), hydrocarbon (HC), and carbon monoxide (CO). It was concluded that the model is effective using data from China. Guor et al. (2020) presented the results of gas emission tests in vehicles and scrutinized the seats, vehicle/total mass, fuel standard, and engine-rated power. Also, the NOx emission, CO emission, and HC emission factors were considered. It was concluded that the emission rate of gas pollutants during the acceleration situation of the diesel tourist bus was higher than the deceleration iteration. Allam and Elsaid (2020) evaluated the pleated air filters having various parameters experimentally and numerically. The operating parameters studied include exhaust gas temperature, brake-specific fuel consumption, and the elapsed time of consuming fuel. Other parametric classes include engine speed, pleat height, fitter medium thickness, dust load, pleat spacing, and air violate. It was found that a lower pressure drop is possible at the air fitter. Bor et al. (2018) analyzed the limit of patterns for emissions through the modification of the engine's contact using real-life situations. It was ascertained that particular compounds were limited and did not reduce the value of the operating parameters. Mqdziel (2023) reviewed the literature on models concerning exhaust gas estimation from vehicles. The work was declared as valuable for future research.

From the above discussion, further studies into vehicle exhaust emissions are necessary. However, it should be skewed toward the packing industry and logistic issues. To address this necessity, the fuzzy concept, 0/1 knapsack dynamic programming model, and the PROMETHEE method in a combined form were used for the optimization and selection problem of vehicle exhaust emission in the packing industry. The input parameters including materials used for packaging, packing units sold, carbon dioxide equivalent of packing materials, revenue attained in the packing industry, compound annual growth rate, and quantity consumed were analyzed to obtain essential information for analysis of the proposed method. Moreover, in the context of road network decarbonization, evaluating the vehicle emissions from vehicles belonging to the packing industry but operating on roads such as in the Indian packing industry considered here is challenging and may be computationally intensive. However, this paper introduces the first fuzzy-0/1 knapsack-PROMETHEE method integrated approach using data obtained from the Indian logistic environment. The method was used for three unique purposes, first to reduce the uncertainty in the input parameters. The second is to optimize the parameters using the knapsack problem. The third aim is to select the best parameter in the process. Overall, the uncertainty reduction, optimization, and parametric selection are conducted concurrently to obtain improved control and monitoring of the vehicle emission process. Furthermore, the contribution of this article is the proposal of a fuzzy-0/1 knapsack-PROMETHEE method that can reduce the uncertainty of the vehicle emission parameters, optimize the parameters for efficiency, establish superior parameters based on desirable criteria, and enrich the theoretical research on decision analysis in general.

The fuzzy -0/1 knapsack-PROMETHEE method has the following advantages:

1. The PROMETHEE method aspect of the integrated method exhibits completeness in ranking. This implies that it has all the essential parts and provides an avenue to compare parameters. Here, benchmarking of parameters is made possible; parameters that require improvements are identified and actions could be taken to enhance them.
2. The part of the proposed method containing the PROMETHEE method makes the whole method to be user-friendly where the method, by design, attempts to generate a positive user experience when the various aspects of the method are evaluated. This means that the user is satisfied with the experience gained and may likely return to use it for other problems.
3. The proposed method is straightforward to understand and use. It often offers optimal solutions concerning the 0/1 knapsack problem component of the method and is also very efficient.
4. The method proposed in the present study allows decision-makers to declare their judgments regarding linguistic variables.

2. LITERATURE REVIEW

This study introduces a new approach to deciding on a green logistic system, particularly for reducing exhaust pipe emissions. However, several relevant literature sources in this area abound. Therefore, to establish the gap that the present study fills the associated studies are reviewed under the following sub-headings: 0/1 knapsack problem, fuzzy 0/1 knapsack problem, and the PROMETHEE method.

2.1. The 0/1 Knapsack Problem

To understand the 0/1 knapsack problem literature, some basics about what constitutes a knapsack problem will be very helpful. As mentioned in Pan and Zhang (2018), the concept of the 0/1 knapsack problem is central to the operations research field and is particularly a theme of discussion in combinational optimizations. Specifically, it is located in the non-polynomial hard problem region. A knapsack problem is described as one in which an opportunity for assessing a set of items abound. These item sets could be allocated weights and values for each item. The issue now is to evaluate the scenario such that the items to include in the collection are determined. However, the condition is that the total weight becomes as large as possible.

Lin et al. (2011) demonstrated the feasibility of reducing a 0-1 linear knapsack problem having a continuous variable to a knapsack problem. The procedure of dynamic programming in COMBO, a novel method, was applied to solve the knapsack problem. This study is relevant to the present research in that the knapsack problem is common to the study and the present work. However, the present study diverges from the research since no integration with the multicriteria method of the PROMETHEE method was made in it. Yet, the PROMETHEE method provides an outstanding interface with the knapsack problem model to further enhance the uncertainty in the vehicle emission process when the fuzzy method was also integrated into both the knapsack problem and the PROMETHEE method. Halman et al. (2023) presented a knapsack constraint-type optimization problem in the realm of max-max, min-min, min-max, and max-min conceptualization where a single numerical parameter was analyzed. This problem claimed to be NP-complete, was analysed and solved. The relevance of the study to the present work is to deployment of knapsack problem solution ideas to solve the optimization problem. Yet it differs from the current study as the present work considers the reduction of uncertainty in the evaluation process using fuzzy concepts integrated with the PROMETHEE and knapsack methods. Unfortunately, it was not considered in the previous study.

Nip et al. (2017) discussed a knapsack problem such that the weights of items are as well variables that should satisfy a set of linear constraints while the capacity of the knapsack is declared to be known and given. Furthermore, two variants of the problem were specified in which approximation algorithms were declared. The interesting extension of the results to diverse knapsack situations having a fixed member of knapsacks as well as similar capacities were analyzed and placed side-by-side of the present paper, the knapsack problematic treatment is common to both articles. However, the current research presents an advantage of integrating knapsack, fuzzy algorithm, and the PROMETHEE scheme, which was absent in the paper being reviewed. Plotkin (2022) discussed the quadratic programming-based knapsack problem that contains a strictly convex separable objective function, two-side constraints on variables, and single linear constraints. The difficulties in the knapsack problem were overcome with the proposed algorithm. Though the contributed knapsack method was useful to the optimization community and advances knowledge, the present study diverges from the reviewed article as it contains additional methods of PROMETHEE and fuzzy algorithm. Salem et al. (2018) implemented the solution to a knapsack problem where conflicts are described as a Disjunctively Constrained Knapsack problem, is defined. A classical development of the problem was contemplated while the constraints and the polytope related to it were analyzed. Based on initial results a branch and cut procedure was introduced to solve the problem. Given the usefulness of the presented study in advancing knowledge on global optimization, it is still desirable to contribute more to the literature by way of additional studies. Thus, the current study is relevant in that it adds PROMETHEE and fuzzy algorithms as two transformation agents for improved selection and the reduction of uncertainty among the parameters.

Mansour (2023) proposed a procedure based on ant colony optimization integrated with the multi-objective local search scheme to obtain a compromise of the intensification with the diversification mechanisms in a formulated knapsack problem. It was concluded that the use of a structure based on multi-dimensionality and a hybrid procedure revealed interesting results and ascertained a superior balance of diversity with convergence. Although the contribution advances the global optimization frontier of knowledge, a unique combination of fuzzy algorithm, 0/1 knapsack problem-solution structure, and the PROMETHEE method presents an additional contribution to knowledge as proposed in the present study. Yildizdan and Bas (2023) solved a formulated knapsack problem in search of a near-optimal solution within a reasonable solution time using the artificial jellyfish search algorithm from a binary analytical perspective. It is called Bin_AJS, which was tested on two datasets. Forty knapsack problems were formulated to attain an optimal value in 97.5% of the problems. The metaheuristic approach is a unique contribution to the literature on knapsack problems. However, the approach falls short in capturing uncertainty, which is an attempt by the present study that integrates the fuzzy algorithm, PROMETHEE method, and 0/1 knapsack problem-solution method. Ballinas and Montiel (2023) contributed a joint model of the quantum genetic algorithm with an adaptive rotation angle to solve the formulated 0/1knapsack problem discussed. It was reported that the quantum procedures exhibited performance close to, but exceeds genetic algorithm when the accuracy of the solution was considered. While the study is a good contribution to the literature, there is no capture of uncertainty in the results and it was not reduced. However, introducing the fuzzy algorithm, in the present work will attain a reduction of uncertainty. Besides, the PROMETHEE method and 0/1 knapsack solution procedure will further enhance the solution.

An interesting development in the knapsack problem conceptualization and solution area is the affirmation that knapsack problem solutions are more effective when two or more methods are combined. This understanding encourages the present authors to combine the PROMETHEE method with the fuzzy algorithm while the central feature of the amalgamation is the knapsack solution model. Thus, in the literature, solutions have been developed for the knapsack problem by amalgamating ant colony optimization with a multi-objective local search scheme (Mansour, 2023), genetic algorithm coupled with an adaptive rotation angle method (Ballin as and Montiel, 2023).

2.2. The Fuzzy 0/1 Knapsack Problem

The fuzzy knapsack problem is the treatment of the knapsack problem in a fuzzy nature (Niksirat and Nasseri, 2022). Moreover, Niksirat and Nasseri (2022) proposed a knapsack that recognizes the objective function and constraints as fuzzy in three different modules: the chance-constrained, the expected value, and the dependent-chance model. They applied the credibility ranking method to convert the fuzzy model into an equivalence of crisp linear structure subject to triangular and trapezoidal fuzzy members. The feasibility of the method was validated using data on pre-disaster investment. While the fuzzy knapsack problem formulated and solved extended the frontier of knowledge in uncertainty reduction and global optimization analysis, further enhancement is required to identify the strength of each parameter on the importance scale. This latter requirement is absent in the article but the present article, which introduces the PROMETHEE method could achieve this objective.

Kasperski and Kulej (2007) formulated a fuzzy optimization problem as a 0-1 knapsack problem having imprecise weights and profits. The parameters that were declared as imprecise were structured as fuzzy intervals. The authors considered a choice solution approach subject to uncertainty and proposed two outcomes for the developed methods. Notwithstanding, the study could benefit from the application of an additional multicriteria method capable of selecting the best parameters such as the PROMETHEE method. Raj et al. (2023) defined a mathematical model for the wholesaling of vegetables from the multi-objective multi-resource problem. Here, it was aimed to reduce time and expand the profit made while the knapsack problem in a fuzzified environment is the principal structure of the method adopted. In the model, the important elements are the cost of travel, demand, and possible profits on the wholesaling of vegetables. The study properly analyzed agricultural products and vegetable wholesaling from the perspective of uncertainty and used the knapsack problem in the formulation. Notwithstanding, the selection aspect of the method could be further strengthened by introducing another multicriteria method such as the PROMETHEE method.

Traneva et al. (2023) applied the intuitionistic fuzzy knapsack problem to an example where the weights of items are expressed as intuitionistic fuzzy values while profits and the knapsack capacity are defined likewise. It was concluded that the example shown properly demonstrated the effectiveness of the method. Moreover, the approach proposed by the authors is useful in capturing uncertainty in the process. However, more gains could be made by incorporating the PROMETHEE method into the existing fuzzy 0/1 knapsack problem structure.

Pramanik et al. (2022) presented a hybrid of fuzzy logic and a genetic algorithm-oriented method for solving the crucial open-pit mining problem. The problem is considered a non-deterministic polynomial-time hard (NP-hard) 0-1 knapsack problem that has uncertain input parameters. It was concluded that the proposed method produced optimum results under fuzzy conditions and could effectively solve the NP-hard knapsack problem. While the study presented an effective platform to combine fuzziness and the knapsack problem, there could be an enhancement in results concerning selection if the PROMETHEE method is integrated into the existing fuzzy – 0/1 knapsack problem structure of the article. Acharyya et al. (2022) proposed a unique 0-1 knapsack problem with fuzziness for vegetable sellers in a rural community. The formulated problem was solved using the ant colony optimization-oriented method within the fuzzy environment. In the formulation and solution, the profit, weight, and total weight capacity of the consumed vegetables were taken as triangular fuzzy members. The approach was successfully implemented with computational data. Moreover, the fuzziness and the knapsack problem were formulated and solved, a unique and improved solution would be to introduce the PROMETHEE method as an additional method in the pursuit of selection results.

Bakrili et al. (2014) analyzed defense project selection by deploying the fuzzy knapsack problem model, which was aided by the quality function deployment and the analytic hierarchy process. Multi-objective problem was used to incorporate the benefit values of the project while the environmental impact values were computed from the quality function deployment method and the analytic hierarchy process aided in the development of the implementation risks for the project. It was concluded that the fuzzy multi-objective goal programming developed was effective. While the combination of fuzzy algorithm and multi-objective goal programming yielded positive results, enhancing the combined model with the PROMETHEE method will be a further enhancement to the results obtained from the defense project selection since the PROMETHEE method was developed in the multi-criteria literature for selection.

Given the above discussion, it is noted that some business environmental parameters such as product demand and profit galloping predetermine uncertainty in the parameters of the wholesaling vegetable problem, considered earlier. Likewise, the present problem of vehicle emission monitoring and control in the packing industry may be formulated using the fuzzy algorithm as part of the structure. In this case, the galloping volume of vehicles plying the road which vehicles of the packing industry plies is an important uncertainty factor affecting the parameters of vehicle emissions. Another factor could be the varying speed of the vehicle as it journeys from the source to the destination. Moreover, the changing weather conditions also predetermine uncertainty. Therefore blending the results of the fuzzy algorithm with the knapsack problem, which is interesting, may be more enhanced if the PROMETHEE method is added to the integration of fuzzy algorithm and knapsack problem.

2.3. The PROMETHEE Method

The tasks of identifying and assessing all aspects of vehicle emission and road decarburization due to the packing industry activities on roads are challenging to the logistics manager in such an organization. Logistics managers are under pressure to ensure that the organization's vehicles released for road transportation minimize the environmental impacts of their particular exhaust pipe emissions in the logistic network and delivery. However, over the years, several important literature sources have been documental, particularly on the PROMETHEE method. Studies in the past have either treated the PROMETHEE method as part of the integrated method used in analysis or on a sole basis. A review of some of these studies follows: Liu and Li (2021) deployed the regret theory and PROMETHEE method as part of a comprehensive analysis of the probable failure risks in green logistics. The main purpose of the PROMETHEE II method inclusion is to produce a final ranking approach for the solved problem. It was reported that grouping and risk attributes of expects that provided inputs to the model should be considered in practical risk assessments. Wei et al. (2023) developed a barrier assessment structure for the forest carbon sink project with an emphasis on China. Specifically, the authors deployed a joint multi-criteria decision-making approach, which established the crucial barriers and developed. The criteria system using the two-phase systematic review in the multicriteria method utilized, the PROMETHEE was a framework, and this was presented as the Gaussian rule involving the BWM-IT2F PROMETHEE II method. The BWM, IT2F, and PROMETHEE II are the short forms of the Best Worst Method, interval type – 2 fuzzy set method, and Preference Ranking Organization Method for Enrichment Evaluations II method, respectively. The outcome is that "Lack of clear leadership" and "Forest management performance" are the most important factors in the system considered. Although the study considered PROMETHEE II in an integrated model to solve the selection problem, the method fails to account for the uncertainty in parameters as suggested in the present study. Govindan et al. (2017) applied the PROMETHEE method to rank suppliers in the food sector in the adoption of a green supply chain management structure. Specifically, the supplier selection problem was formulated and the PROMETHEE method was used in the green purchasing aspects of the field while the decision makers' preferences were incorporated into the solution framework. The effectiveness of the PROMETHEE method was enhanced by integrating robustness analysis, procedures for developing group compromise ranking, and the Simos procedure. It was concluded that the method is applicable, valid, and robust when the data from the Indian food industry is used for the problem formulation and solution. The relevance of the present study to this reviewed study is in the application of the PROMETHEE method, which is common to the studies. In addition, the packing industry considered in this work, which entails wrapping, and sealing of boxes for products may be for the food industry. Nonetheless, the present study appears to have an added perspective, which is an integration of the optimization concept of 0/1 knapsack problem and reduction of uncertainty of parameters, which is achievable using the firry algorithm. Tong et al. (2022) introduced and enhanced the PROMETHEE II method is a supplier selection endeavor within the small and medium enterprises in China. The three perspectives of risk factors, product and service capability, and cooperation degree were used to determine the assessment structure for sustainable supplier selection. Also, the extended PROMETHEE II method was generated by integrating the classical PROMETHEE method with probability language term set and subjective preference parameters. It was concluded through a practical case and sensitivity analysis that the result of the method and its applicability is effective in the situation studied. The common element of the method and the present study is the use of the PROMETHEE method. However, despite the enhancement to the PROMETHEE II utilized in the study, the issues of optimization of parameters and reduction of uncertainty in parameters were downplayed. This gap is attempted to be bridged in the present study through the introduction of the 0/1 knapsack problem and fuzzy algorithm in an integrated method proposed by the present authors for a solution to the vehicle emission problem where zero net emission is the target.

3. METHODOLOGY

3.1. The Packing Industry

The packing industry builds containers and boxes appropriate to transport products through roads, rails, and water bodies such as waterways. However, road logistics is of interest to the present researchers. Through roads, a substantial amount of carbon emissions are involved and road logistics operators, using vehicles emit carbon particles that threaten the environment. Moreover, these road logistic operators must align with governments and customers to decarbonize the roads and environment from their actions aiming at the broader global drive towards net zero. Decarbonization of road logistics which is emphasized through several routes, including battery technologies, charging solutions, and alternative fuel usage is emphasized in the study through vehicle emission control for those vehicles still depending on fossil fuels.

3.2. The Basis for the Integration of Fuzzy Algorithm, 0/1 Knapsack Problem, and PROMETHEE Method

Several reports on vehicular emissions on road networks reveal that zero net emission in communities with road networks is a crucial concern of all stakeholders, such as the governments, regulatory agencies, and the packing industry whose vehicles play the road networks. Moreover, a couple of reports within the green logistics system emphasize the uncertainty in vehicular emission process parameters as a dominant factor in decision analysis and regulating the performance of a system. For instance, Raj et al. (2023) declared that the application of fuzzy concepts reduced the uncertainty in the wholesaling of vegetables with particular emphasis on parameters such as profits, cost of travel, and demand. It was implied that excluding the use of fuzzy algorithms threatens decision analysis and the possibility of making wrong judgments. Consequently, they declared that it is essential to formulate and solve uncertainty reduction problems to accurately undertake correct decisions and then the utmost system goal of enhanced performance for the system could be achieved. However, while the research on fuzzy algorithm, concerns promotes uncertainty reduction, there exists a significant research discussion that advocates for optimization through the application of 0/1 knapsack problem. For instance, Traneva et al. (2023) provided evidence in this regard as the integrated fuzzy and the knapsack problem. This effort, among other similar publications, had concurrently reduced uncertainty in parameters while optimizing the parameters. Unfortunately, there has not been any meeting point to integrate the ideas of this latter research thoughts vis-à-vis the merging of fuzzy algorithm and 0/1 knapsack on one hand and its synergy of ideas with the PROMETHEE method. Thus, it is compelling to integrate these two ideas in the development of a decision analysis model, which captures the uncertainty, optimization, and selection parameters. Furthermore, the decision model of vehicle emission evaluation would be the best fit analytical instrument to assist in emission control decisions from the vehicle exhausts. This is a concern in the present study. The fuzzy-0/1 knapsack-PROMETHEE method is a useful tool in the industry. So, the fuzzy-0/1 knapsack problem-PROMETHEE method is an approach useful for the vehicle emission problem in the packing industry in a match towards zero net emission in road networks. The proposed method is deployed in the present study with data drawn from the packing industry in India.

3.3. PROMETHEE Method

The purpose of the PROMETHEE method is to find the preference ranks from the different levels of six input parameters for greenhouse gas emissions. This is illustrated with a practical case in Benrajesh and Rajan (2019). In particular, the data was obtained from Table 1 of Benrajesh and Rajan (2019).

In the following section, the steps used to implement the PROMETHEE method are indicated:

Step 1. Normalize the evaluation matrix (decision matrix).
Normalized value (for beneficial criterion) gives.

$$R_{ij} = \frac{(X_{ij} - \min X_{ij})}{(\max X_{ij} - \min X_{ij})} \tag{1}$$

where $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$
Normalized value (for non-beneficial criterion) gives

$$R_{ij} = \frac{(\max X_{ij} - X_{ij})}{(\max X_{ij} - \min X_{ij})} \tag{2}$$

where $i = 1, 2, \ldots, m$; j = 1, 2, …, n

Step 2. Calculate the evaluation difference of the ith alternative with respect to other alternatives.

Step 3. Calculate the preference function, Pj(a, b), where
Preference Criteria: Criterion 1
$P_j(a,b) = 0$ If $R_{aj} \le R_{bj}$, then $D(L_a - L_b) \le 0$ (3)
i.e. if the alternative difference is less than zero, input 0 as the outcome across parameters
$P_j(a,b) = 0$ If $R_{aj} \ge R_{bj}$, then $D(L_a - L_b) \ge 0$ (4)
i.e. if the alternative difference is greater or equal to zero, retain the difference of alternative value as an outcome across parameters.

Step 4. Calculate the aggregated preference using Equation (5):

$$\pi(a,b) = \frac{\sum_{j=1}^{n} W_i P_j(a,b)}{\sum_{j=1}^{n} W_i} \tag{5}$$

where W_j is the weight.

Step 5. Calculate the leaving and entering outranking flows, Equations (6) and (7):
Leaving (positive) flow for ath alternative,

$$\varphi^{+} = \frac{1}{m-1}\sum_{b=1}^{m} \pi(a,b) a^{n-k} \tag{6}$$

Entering (negative) flow for ath alternative,

$$\varphi^{-} = \frac{1}{m-1}\sum_{b=1}^{m} \pi(a,b) a^{n-k} \tag{7}$$

for example, $a \neq b$.

Step 6. Calculate the net outranking flow for each alternative.
$\text{Ø}(a) = \text{Ø}^{+}(a) - \text{Ø}^{-}(b)$ (8)

Step 7. Determine the ranking of the considered alternatives based on the values of Ø (a).

Step 8. Compare outrank flows with criteria.

Step 9. Eliminate all incomparable from the list obtained in step 8.

3.4. Procedure for Implementing 0/1 Knapsack Problem Dynamic Programming

To understand the procedure followed in implementing the 0/1 knapsack problem, it is essential to first define what the problem constitutes. The description, which follows is a good fit for the 0/1 knapsack problem: "Consider there are objects to analyze for weights, values and other measures. Suppose there is a total weight of all the objects known. There are also weights for each of the objects and the corresponding values, which could be some other measures such as the cost of the material. The concern is how to pick items from the various objects in a way that the sum of their values is maximum while the sum of the weight is less than or equal to the total weight. The assumption is that there is just one quantity of each item. The "0/1" term in 0/1 knapsack problem implies that one may decide not to pick the item, where the classification is "0" or may pick the item where the classification is "1". In any case, the researcher cannot split the item. Furthermore, dynamic programming is used to solve the problem.

Step 1. Notice that this is a situation where items are considered at different times. Observe the new item that comes in and decide whether this item is to be picked or not.

Step 2. Search for the item that yields the maximum value.

Step 3. If the item is picked, the maximum value is then taken as the value of the item with any value obtained from a subtraction task. By subtraction, the researcher refers to the removal of the value from the total weight but excluding this item. Alternatively, this could be achieved by considering the best, which can be done while including this item or together traction. By subtraction, it means that the value will be removed from the total weight but excluding this item. Alternatively, this could be achieved by considering the best that can be done without including this item or together.

3.5. Fuzzy Analytical Hierarchy Process Implementation Procedure

The proposal in this work is the fuzzy-0/1 knapsack problem-PROMETHEE method and the fuzzy aspect is represented by the fuzzy analytic hierarchy process (AHP) method, which is the geometric mean value variant of the approach. The fuzzy AHP method has its basis in translating linguistic terms, represented on a fuzzy scale of importance, to membership function. The adopted membership function in this work is the triangular membership function, which is distinct from other types such as trapezoidal or Gaussian membership functions. The choice of triangular membership function indicates that three points represent the fuzzy member, represented as l, m and u for the lower, middle and upper values of the fuzzy member, respectively. While the fuzzy value is shown in Equation (9), it is supported by six different scales of 0,1,2,3 and 4 for "No importance,", "Equal importance", "Moderate importance", "strong importance", and "very strong importance", respectively. However, intermediate values are represented as 0.5, 1.5, and 2.5, respectively.

$$\mu\overline{A} = \overline{A} = (1, 2, 3) \text{ fuzzy numbers} \tag{9}$$

Furthermore, the first step in the application of the fuzzy analytic hierarchy process (AHP) method is as follows. Also, other steps are stated.

3.6. Implementation of the Fuzzy-0/1 Knapsack Problem Dynamic Programming-PROMETHEE Method

In a previous article, by Agada et al. (2024), the fuzzy algorithm, 0/1 knapsack problem, and EDAS method were implemented with the method explained in detail. However, the same data utilized in the study was used here and the procedure and implementation of the fuzzy algorithm and the 0/1 knapsack problem are the same in the paper and the current paper. Thus, the current study adopts the procedure of both the fuzzy algorithm and the 0/1 knapsack problem here. However, the appendage to this is the PROMETHEE method, which was not treated in Agada et al. (2024) but fully explained in the current study. Moreover, a brief explanation of the fuzzy algorithm is made in the present article while this idea is integrated into the 0/1 knapsack problem and PROMETHEE method discussed in the present study. Thus, what follows are the additional details provided in this work on the implementation of the fuzzy – 0/1 knapsack problem – PROMETHEE method discussed in the present work.

To implement the procedure for the fuzzy 0/1 knapsack, the start is with the fuzzy algorithm. It implies that a decision needs, to be made on the fuzzy class to use. Thus, the research may utilize fuzzy geometric or fuzzy synthetic types. However, in general, they commence with making decisions obtainable from the decision maker. The researcher decided on who the decision makers were. These decision-makers should be relevant to the process. Nonetheless, before the decision maker can make decisions, there is a need for an evaluation matrix. In this particular case, the terms extreme low to extreme high are the range of decisions made by the researchers. The extreme low assumes the value of 0 to 0.1. The very low has a range of values of 0.1 to 0.3. Then, for the linguistic term, low, it has a range of 0.3 to 0.5. Then medium ranges from 0.5 to 0.7. High has a value of 0.7 to 0.9. Very high has a value of 0.9 to 1. However, extremely high is 1. The matrix used to generate these digits is obtained from the membership functions, which is taken as the triangular membership function consisting of three entries called the fuzzy numbers, which may be converted into crisp numbers. The decision maker is then made to decide on each of the parameters involved in the process. Then a table has to be generated for each of the decision makers concerning the different parameters A to F. Each of the decision makers will make a decision based on the evaluation rating ranging from extremely low to extremely high. After this, the researchers substitute the linguistic terms with numerical values in a tabular form. Based on the rating matrix, the researchers obtain values for lower values, middle values, and upper values of the fuzzy numbers. The next step is to find the fuzzy aggregate, which considers a matrix of parameters against the lower values, middle values, and upper values. The lower values are obtained by finding the averages for the lower boundaries of each decision maker’s estimates. This procedure is repeated for the middle values and the upper values. From the results, it may be realized that the fuzzy aggregate values were in several decimal points with few whole members. This may suggest the need to attempt a different fuzzy aggregate to possibly obtain more approximated numbers. In this case, the researchers obtain the minimum value from the following explanation. Notice that all decision-makers have already given their ratings based on each parameter. The least or minimum rating is then picked as the fuzzy aggregate value. The same is repeated for the middle and upper values. Then, the averages of lower, middle, and upper values are calculated to obtain the normalized fuzzy aggregate value. After this, multiply the values obtained from the fuzzy aggregate with the 0/1 knapsack dynamic program value. Notice that the procedure for obtaining the 0/1 knapsack problem has been earlier obtained in this section. With the columns for the lower, middle, and upper values, and based on the six parameters considered, an input parametric table is then created for the

PROMETHEE method.

4. RESULTS AND DISCUSSIONS

This section contains PROMETHEE analysis on Green House Gas Emission (GHGE) and we will discuss the data used to verify our method as extracted from Benrajesh and Rajan (2019) with Table 1 containing the input parameters.

The parameters mentioned in Table 1 are defined as follows:

A = Revenue attained in the packing industry for a year (million dollars).
B = Packing units Sold (Billion).
C = Compound annual growth rate (2015).
D = Materials used for packing.
E = Quantity consumed in Kilo tons.
F = Carbon dioxide equivalent of Packing materials.

Furthermore, Table 1 provides the input parameters for the PROMETHEE analysis. PROMETHEE is an abbreviation for preference ranking organization method for enrichment evaluation which has two types; PROMETHEE 1 and PROMETHEE 2. Our initial analysis will begin by implementing PROMETHEE 2. This is because PROMETHEE 2 is known for arriving at a full/complete ranking as compared to PROMETHEE 1 which results in giving a partial ranking without much details on the least ranked alternative. Partial ranking refers to the ordering of the parameters for emission which reveals ties. To explain this situation; consider four out of the six input parameters that represent exhaust emissions for the problem being solved in the work. These parameters are A, B, C, and D. Assuming that the ranking result given out is such that C is greater than B while B is equal to D and D is greater than A, then the ranking is defined as partial. It means that not all the parameters can be placed in importance one to another. If the ranking is closely observed, there is no importance order between B and D. However, if the ranking is complete, we may have a situation where C is greater than B while B is greater than D and D is greater than A. Moreover, the attraction to PROMETHEE is because there is a complete ranking of the parameters.

In Table 1, each parameter is identified by levels 1, 2, and 3. The experimental values for each parameter are generated in a defined number of points which could be divided into parts, which are lower, middle, and higher. The midpoint of each of these parts will represent the level. For a beneficial criterion, the mean of the lower part is less desirable than the mean of the middle part. Likewise, the means of the middle part as well as the lower part are less desirable than the mean of the higher part. The meaning of this is that, if any of the lower or middle values is chosen it means that the system is suboptimal. For the non-beneficial criterion, the reverse of the declaration of values regarding what is desired from lower, middle, and upper points is the case. In this particular case, the six input parameters considered, namely A, B, C, D E, and F are linked to the corresponding values. To illustrate the meaning of the parametric-level-linkage, it is observed that row 2 in Table 1 which contains values of 52, 127, 0.77, 1.5, 5581, and 1 corresponds to input parameters A, B, C, D, E, and F respectively for alternative level 1.

Furthermore, the table used in the present case assumes that the behavior of each parameter is linear, usually growing from level 1 to the last level, which is level 3. Although this pattern of data is observed in the most available analysis in the literature, the present researchers caution other researchers not to think of this pattern alone. In reality, the pattern may take any of the functional behaviors referred to by the researcher. For instance, if the pattern is sinusoidal it means that level 1 may be at a value that is greater than level 2 but level 2 is less than level 3. This defines an ill and valid situation. To fulfill the next step, which is normalization, the minimum value for a parameter along the three-level point is determined. This means that for each parameter, it is expected to obtain the minimum and maximum points. However, experience shows that it is possible to have all three values for the levels concerning a parameter to be equal. This is not good for the calculations. The six input parameters A, B, C, D, E, and F are represented by their corresponding levels (1, 2 &3). The minimum (row 6) and maximum (row 7) values for each parameter are also specified, which will be used in the normalization process.

Notice that the normalization of each evaluation value ( ) in Table 1 for a particular alternative was obtained using either Equation (1) or Equation (2). This depends on whether the parameter considered is beneficial or non-beneficial. Notice that when all the parameters are considered, those that are desired to increase in value are parameters A, B, C, and E. They are called beneficial parameters. Moreover, two other parameters are not expected to increase in value, notably parameters D and F, which are called non-beneficial parameters. Table 2 shows the result of the normalization evaluation matrix.

To illustrate how to obtain the value of 0 for the interaction of the parameter A and level 1, the following is useful. Notice that we are considering parameter A which is a beneficial criterion. The normalized value is obtained by first reading the value from Table 1, which is 52. However, to obtain the numerator, the minimum for parameter A is identified as 52. Therefore, the numerator is zero. Also, the denominator is 0, which was obtained when 52 is subtracted from 52. The overall result for parameter A under level 1 is then 0. The above procedure for normalizing the evaluation matrix for parameter A was repeated for other beneficial parameters B, C, and E to obtain [0, 0.5, 1], [0, 0.5150, 1], and [0, 0.5000, 1], respectively. Note that in normalization methods, the two aspects usually considered are the beneficial perspective and the non-beneficial viewpoint. Having discussed the beneficial perspective, it is time to explain how the non-beneficial perspective is implemented in this work. Explaining from Table 1, if the normalized value of parameter D and level 1 intersection is to be computed, the following tasks are accomplished. Along the column for parameter D, the maximum is first determined, which is 3.5. The actual value in the cell of parameter D and level 1 is 1.5. Next, the minimum value along column D is 1.5. By applying the non-beneficial normalization index, the numerator is (max) – , which is 3.5 – 1.5. Next, the denominator is computed as max – min , which is 3.5 –

Table 1. Input Parameters from Benrajesh and Rajan (2019)

Level	Input Parameters					
	A	B	C	D	E	F
Level 1	52	127	0.77	1.5	5581	1
Level 2	171	1494	16.00	2.5	43666	12300000
Level 3	287	2861	30.34	3.5	81750	24600000
Min	52	127	0.77	1.5	5581	1
Max	287	2861	30.34	3.5	81750	24600000

Table 2. Normalizing evaluation matrix

Level	Input Parameters					
	A	B	C	D	E	F
Level 1	0.0000	0.0000	0.0000	1.0000	0.0000	1.0000
Level 2	0.5064	0.5000	0.5150	0.5000	0.5000	0.5000
Level 3	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000

Table 3. Evaluating difference of the i^{th} alternatives with respect to others

Level	Input Parameters					
	A	B	C	D	E	F
L1-L2	-0.5064	-0.5000	-0.5150	0.5000	-0.5000	0.5000
L1-L3	-1.0000	-1.0000	-1.0000	-1.0000	-1.0000	-1.0000
L2-L1	0.5064	0.5000	0.5150	-0.5000	0.5000	-0.5000
L2-L3	-0.4936	-0.5000	-0.4850	0.5000	-0.5000	0.5000
L3-L1	1.0000	1.0000	1.0000	-1.0000	1.0000	-1.0000
L3-L2	0.4936	0.5000	0.4850	-0.5000	0.5000	-0.5000

Table 4. Preference function

Level differences	Input Parameters					
	A	B	C	D	E	F
L1-L2	0.0000	0.0000	0.0000	0.5000	0.0000	0.5000
L1-L3	0.0000	0.0000	0.0000	1.0000	0.0000	1.0000
L2-L1	0.5064	0.5000	0.5150	0.0000	0.5000	0.0000
L2-L3	0.0000	0.0000	0.0000	0.5000	0.0000	0.5000
L3-L1	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000
L3-L2	0.4936	0.5000	0.4850	0.0000	0.5000	0.0000

1.5. By dividing the numerator by the denominator, i.e. 2.5/2.5, we obtained the value 1 to be placed in the intersection of D and level 1. The same procedure is followed to obtain values for parameters D-level 2, D-level 3, and all other entries associated with the intersection of parameter F with levels 1, 2, and 3. Following step 1 is the need to evaluate the differences between one alternative from other alternatives, which is discussed in step 2. Notice that the above procedure for normalizing the evaluation matrix for parameter D was repeated for non-beneficial parameter F to obtain [1, 0.5000, and 0]. Step 2 involves the calculation of the evaluative difference of ith alternative with respect to other alternatives. Table 3 is generated from Table 1 by calculating the evaluative difference of each level alternative with respect to other alternatives across the six input parameters A, B, C, D, E, and F.

In Step 2, the results obtained from Table 2 are now used to establish the differences between parameters at various levels. Computational steps are made such that the other levels apart from the one being treated are subtracted from the level of concern for each of the parameters. This means that regarding level 1, the first row will be level 1 minus level 2, shortened as L1 – L2. Still, the next row will be level 1 minus level 3. Now moving to level 2, the third row will be level 2 minus level 1. The fourth row will be level 2 minus level 3. Moving to level 3 on the fifth row the value of level 1 is subtracted from level 3 as L3 – L1. Also, the sixth row is level 3 minus level 2. Now applying these descriptions to the beneficial and non-beneficial parameters, we have the following: For beneficial parameter A, to calculate the value of the intersection between parameter A and L1–L2, the following may be useful. Along the column: the value in parameter A versus level 1 interaction from Table 2 is 0 while the value obtained from parameter A versus level 2 is 0.5064. Then L1 – L2 is 0 –0.5064, which is -0.5064. This value is to be put in Table 3 at the parameter A versus (L1 – L2) intersection. The procedure is followed to obtain other values (parameters B, C, D, E, and F) in the table. Moving on, step 3 is implemented.

This involves the calculation of the preference function. The preference function is obtained by considering preference criteria concerning values obtained in Table 3 and then evaluating the differences for

Table 5. Aggregate Preference function (WGT SYS)

Weightage	0	0.0222	0	0	0.9778	0	Sum
	A	B	C	D	E	F	
L1-L2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L1-L3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L2-L1	0.0000	0.0111	0.0000	0.0000	0.4889	0.0000	0.5000
L2-L3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L3-L1	0.0000	0.0222	0.0000	0.0000	0.9778	0.0000	1.0000
L3-L2	0.0000	0.0111	0.0000	0.0000	0.4889	0.0000	0.5000

different level alternatives across all input parameters. Here, Equations (3) and (4) are applied to obtain Table 4.

For the preference function, we are working with two criteria, namely, the criterion that the alternative difference is less than zero (criterion 1) and the criterion that the alternative difference is more than zero (criterion 2). Criterion 1 aims at eliminating negatives while criterion 2 retains its initial value. To apply these two criteria to produce Table 4, Table 3 is relied upon. The first column in Table 4 is a repetition of what Table 3 contains in the first column. To obtain the parameter A versus L1–L2 interaction of Table 4, the value of -0.5064 is considered. By criterion 1, this value is less than zero, and zero should be used to replace it in Table 4. By moving down along the column of parameter A, the parameter A versus L1-L2 intersection is considered, which gives a value of -1. Again, this value is less than zero and should return zero to Table 4. However, a different situation is encountered when the value to be replaced at the L2 – L1 intersection is considered. The original value in this cell is 0.5064. Since the value is more than zero, it is retained. Notice that this is the application of criterion 2. Notice that the preference functions Pj(a,b) for parameter A in Table 4 are with respect to the differences of alternatives (level 1, level 2, level 3) from Table 3. The above procedure for the preference functions for parameter A in Table 4 with respect to evaluative differences of alternatives (level 1, level 2, level 3) from Table 3 is repeated for other parameters B, C, D, E and F to obtain [0, 0, 0.5, 0, 1, 0.5], [0, 0, 0.5150, 0, 1, 0.4850], [0.5, 1, 0, 0.5, 0, 0], [0, 0, 0.5000, 0, 1, 0.5000], [0.5000, 1, 0, 0.5000, 0, 0], respectively.

This involves the calculation of the aggregate preference function, step 5. The aggregate preference function is obtained by the aggregate sum of the multiplication of weightages with the preference function values (weighted preference function) obtained from Table 4 across all input parameters divided by the sum of all weightage values. Table 5 is generated by obtaining the aggregate preference function of input parameters [A, B, C, D, E, and F] with respect to the weightage value of combined Fuzzy extent synthetics and 0/1 Knapsack dynamic programming [0, 0.022249, 0, 0, 0.977751and 0] respectively across all preference functions.

Previously, we have obtained a single method called fuzzy extent synthetics-0/1 knapsack dynamic programming which was used on the data having six input parameters from Benrajesh and Rajan (2019). This generated values of 0, 0.022249, 0, 0, 0.977751 and 0. These weights are to be multiplied with the results obtained from PROMETHEE in Step 3 of the procedure for this work. Table 5 shows the presentation format to obtain values along the rows of L1-L2, which are under A, B, C, D, E, and F. The weight is multiplied by each of the values in Table 4 to obtain the values in Table 5. Consider the value to put at the intersection of L1-L2 and parameter A, the weight for A, which is 0 is multiplied by the value at this intersection in Table 4. This gives a value of 0. Likewise, by multiplying the weight of parameter B with the original value at the intersection of L1-L2 and parameter B, A value of 0 is obtained. The procedure is then followed to fill Table 5. Next, the values along all rows are summed and put under the last column. Consider the first row represented by L1-L2, the sum of values under each of the parameters is 0. The same approach to summation is applied to the various levels until we reach the last row that contains L3-L2 and the sum of all the parameters is equal to 0.49999358. (Table 6)

Now, the stage is set to determine the leaving and entering variables. To do this, the six rows are collapsed to three by summing two rows at a time. In this case, rows 1 and 2 contain level 1 as the first component of each subtraction. Therefore, they have to be merged. By redrawing the table we will have the first two levels written as level 1 and the sum is 0. Next, the level 2 values are contained in rows 3- and 4 with the sum of 0.50000642. Level 3 is obtained from rows 5 and 6 with the sum of 1.49999358. A further calculation is made such that the formula in Equation (5) is used. The idea of Equation (5) is that m is taken as 3 being the maximum number of levels used in this work. Therefore the factor 1/ (m-1) gives 0.5 when m = 3. This value of 0.5 will be used to multiply the earlier summed-up values of levels 1, 2, and 3 which are 0, 0.5000, and 1.5000, respectively. The result is 0, 0.2500 and 0.7500. These computations are for leaving variables. These results are shown in Table 6.

Now to complete Table 6 with the various values, consider the intersection of L1 and L1, the value being put there is "_" because the intersection of L1 with itself is non-existent. Still on level 1 with its intersection with level 2, the value of 0, which is the sum, is then put under that intersection. The hint used to understand this is to look at the different levels subtracted from each other i.e. L1-L2 and L1-L3. Next, the intersection between levels 1 and 3 is 0 because we picked from the second row (L1-L3). To obtain values for level 2, we start with the intersection of level 2 and level 1 to obtain 0.5000 which is the sum displayed at the end of the row containing L2-L1. The intersection of level 2 with itself is indicated with a "_". Moreover, the intersection of level 2 with level 3

Table 6. Leaving and entering flow for i^{th} alternatives

Level	Level 1	Level 2	Level 3	Leaving
Level 1	-	0.0000	0.0000	0.0000
Level 2	0.5000	-	0.0000	0.2500
Level 3	1.0000	0.5000	-	0.7500
Entering	0.7500	0.2500	0.0000	-

Table 7A. Alternative difference outranking flow and ranking

Level	Leaving	Entering	Difference	Rank
Level 1	0.0000	0.7500	-0.7500	3
Level 2	0.2500	0.2500	6.4183E-06	2
Level 3	0.7500	0.0000	0.7500	1

Table 7B. Comparing GHGE (Benrajesh and Rajan, 2019) with fuzzy synthetic (triangular) - 0/1 knapsack dynamic - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy extent synthetic (triangular) – 0/1 knapsack dynamic – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.50	3.50
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

Table 7C. Comparing GHGE (Benrajesh and Rajan, 2019) with a fuzzy geometric mean (triangular) - 0/1 knapsack dynamic - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy geometric mean (triangular) – 0/1 knapsack dynamic – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.5	3.5
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

could be traced back to Table 5 where the fourth row containing L2-L3 has 0 at the extreme. Furthermore, the intersection of level 3 and level 1 is also read from Table 5 under the sum column (row 5) which is 1. Also, the intersection of level 3 and level 2 gives a sum of 0.5000 which is on row 6. Finally, the intersection of level 3 and level 3 is a "_". As we compute the entering variable, equation 6 is deployed where m remains 3 and the index [1/(m-1)] gives 0.5. It then means that feasible values 0.5000 and 1 will be averaged in column 1 to obtain 0.7500. This is called the entering variable of level 1. For levels 2 and 3, the same procedure is applied and the entering variables are obtained as 0.2500 and 0, respectively.

The next step is to calculate the net outranking flow for each alternative. In doing this, Table 7A is developed in which the first column accounts for all the levels, notably, levels 1, 2, and 3. The next column is for the leaving variables. These values are extracted from Table 6. Next, the column for entering variables is created. The next two columns are created with the first column showing the differences between the leaving and entering variables. The second column shows the ranks of the different levels. From the result obtained, the highest difference was obtained for level 3 while it is ranked 1st, level 2 is ranked 2nd, and level 2 is ranked 3rd with the corresponding difference of 0.7500, 6.4183E-6 and -0.7500, respectively. To pick the best result, level 3 is the focus. However, efforts are made to relate level 3 to parameters. It then means that in the original table by Benrajesh and Rajan (2019), level 3 values for all the parameters should be adopted. The result is shown in Tables 7B to 7I.

Recall that parameter C is noted as a beneficial criterion that is meant to increase. Based on the value FES-0/1KDP-PROMETHEE is preferred compared to greenhouse gas emissions by Benrajesh and Rajan (2019), being that its value is greater while more importance/preference is given to greenhouse gas emissions with respect to parameters D and F which are non-beneficial criteria that are deemed to decrease in value. That is greenhouse gas emissions have lower values compared to FES-0/1 KDP-PROMETHEE. Also, the same result is obtained for the following weightage

Table 7D. Comparing GHGE (Benrajesh and Rajan, 2019) with fuzzy extent synthetic (trapezoidal) - 0/1 knapsack dynamic - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy extent synthetic (trapezoidal) – 0/1 knapsack dynamic – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.5	3.5
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

Table 7E. Comparing GHGE (Benrajesh and Rajan, 2019) with fuzzy geometric mean (trapezoidal) - 0/1 knapsack dynamic - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy geometric mean (trapezoidal) – 0/1 knapsack dynamic – PROMETHEE II
1	A	287	171
2	B	2861	1494
3	C	16	16
4	D	1.5	2.5
5	E	81750	43666
6	F	1.23×10^7	1.23×10^7

Table 7F. Comparing GHGE (Benrajesh and Rajan, 2019) with fuzzy extent synthetic (trapezoidal) - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy extent synthetic (trapezoidal) – dynamic – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.5	3.5
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

Table 7G. Comparing GHGE (Benrajesh and Rajan, 2019) with Fuzzy Geometric Mean (Trapezoidal) - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy geometric mean (trapezoidal) – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.5	3.5
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

values: Fuzzy Geometric mean(triangular) - 0/1 Knapsack Dynamic - PROMETHEE II, Fuzzy Extent Synthetic(trapezoidal) - 0/1 Knapsack Dynamic - PROMETHEE II, Fuzzy Extent Synthetic (trapezoidal) Dynamic - PROMETHEE II, Fuzzy Geometric Mean (Trapezoidal) - PROMETHEE II, Fuzzy Extent Synthetic (Triangular) - PROMETHEE II and Fuzzy Geometric Mean(triangular) - PROMETHEE II displayed in Table 7B to 7I, respectively.

From Table 7E, it is inferred that the greenhouse gas emission method by Benrajesh and Rajan (2019) should be given more preference as compared to the Fuzzy Geometric Mean (trapezoidal) - 0/1 Knapsack Dynamic - PROMETHEE II because most its values for the beneficial parameters A, B, C and E are higher and its non-beneficial parameters D and F performs at least equal as compared to the researcher's values.

Furthermore, it was earlier mentioned that the PROMETHEE II technique gives a full ranking while the PROMETHEE I technique gives a partial ranking which will be discussed hereafter in step 7. This step is concerned with the ranking of all the alternatives considered, depending on the values of Ω. Recall that what distinguishes PROMETHEE II from PROMETHEE

Table 7H. Comparing GHGE (Benrajesh and Rajan, 2019) with Fuzzy Extent Synthetic (Triangular) - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy extent synthetic (triangular) – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.5	3.5
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

Table 7I. Comparing GHGE (Benrajesh and Rajan, 2019) with Fuzzy Geometric Mean (triangular) - PROMETHEE II

S/N	Controlled parameters	Green house Gas Emission (Benrajesh and Rajan 2019)	Fuzzy geometric mean (triangular) – PROMETHEE II
1	A	287	287
2	B	2861	2861
3	C	16	30.34
4	D	1.5	3.5
5	E	81750	81750
6	F	1.23×10^7	2.46×10^7

Table 8. Leaving and entering Flow for ith Alternatives (PROMETHEE I)

Level	Level 1	Level 2	Level 3	Leaving
Level 1	-	0.0000	0.0000	0.0000
Level 2	0.5000	-	0.0000	0.5000
Level 3	1.0000	0.5000	-	1.5000
Entering	1.5000	0.5000	0.0000	-

Table 9. Leaving and entering outrank flow with criteria (PROMETHEE 1)

Level	Leaving	Entering
Level 1	0.0000	1.5000
Level 2	0.5000	0.5000
Level 3	1.5000	0.0000

I is that in finding the leaving and entering flow, the alternative matrix values are summed up without finding their averages. Then recall that in Table 6 we attempted to find the leaving and entering flow rank. However, the formula for obtaining the leaving outrank flow is in Equation (7). While the entering outrank flow is in Equation (8). Then compute the entering and leaving flow variables such that their average will not be found.

As illustrated in Table 8. Table 8 is made up of a 3x3 matrix of the alternative levels 1,2 and 3. The understanding of Table 8 is explained earlier in Table 6 but the difference is that in finding the leaving and entering outrank flow, the values are summed instead of finding their mean. The next step is to obtain the outrank flow ranking which is the difference between the leaving and entering variables while comparing with a set of criteria. In this particular case, 3 different criteria are considered. They are differentiated from one another by their relationships of leaving and entering variables. The relationships are illustrated in equations 9, 10, 11, 12, 13 and 14. Furthermore, we shall compare our leaving and entering values in Table 9 with each other using the aforementioned criteria above. This resulted in us obtaining that level 2 is preferable to level 1, level 3 is preferable to level 1 and level 3 is preferable to level 2 without any definite detail on ranking and no further details on these preferences being obtained which makes it partial (see Table 10 and 11).

Table 9 is extracted from Table 8. The leaving and entering values across the three alternatives from Table 9 are compared using the listed criterion of "preferable situation", "Indifference situation" and "incomparable situation".

Mapping alternatives as:

Level 1-Level 2 or Level 2-Level 1 or Level 3-Level 1

Level 1-Level 3 or Level 2-Level 3 or Level 3-Level 2

The above PROMETHEE analysis was done using 0/1 knapsack-fuzzy extent synthetically generated weightage in step 4 as 0, 0.0222, 0, 0, 0.9778, 0 for the six exhaust input parameters A, B, C, D, E, and F. In the course of PROMETHEE analysis, we considered eight weightage values corresponding to the six input parameters from Benrajesh and Rajan (2019) as shown in Table 12.

The listed weightages in Table 12 were applied to the PROMETHEE analysis while repeating steps 4 to step 9 of the PROMETHEE method. The principal findings of this work are as follows:

Table 10. Results of comparing preference using Criterion 2

Level 1 compared to other alternatives	Result	Level 2 compared to other alternatives	Result	Level 3 compared to other alternatives	Result
Level 1 – Level 2	No match	Level 2 – Level 1	2P1	Level 3 – Level 1	3P1
Level 1 – Level 3	No match	Level 2 – Level 3	No match	Level 3 – Level 2	3P2

Table 11. Ranking of leaving and entering flow

Ranking	Level
Level 2 is preferred to Level 1	2P1
Level 3 is preferred to Level 1	3P1
Level 3 is preferred to Level 2	3P2

Table 12. List of weightages used for PROMETHEE analysis

Methods	A	B	C	D	E	F
1*	0.0000	0.0314	0.0000	0.0000	0.9686	0.0000
2*	0.0000	0.2000	0.0000	0.0000	0.0000	0.0000
3*	0.0000	0.1290	0.0000	0.0000	0.8710	0.0000
4*	0.2000	0.2000	0.2000	0.2000	0.0000	0.2000
5*	0.1953	0.2340	0.1476	0.1407	0.0359	0.2463
6*	0.1621	0.1621	0.1621	0.1893	0.1621	0.1621
7*	0.1745	0.2062	0.1341	0.1072	0.1448	0.2332

Key 1* - Fuzzy geometric mean – 0/1 knapsack dynamic programming
Key 2* - Fuzzy extent synthetics and 0/1 knapsack dynamic programming (trapezoid membership function)
Key 3* - Fuzzy geometric mean - 0/1 knapsack dynamic programming (trapezoid membership function)
Key 4* - Fuzzy extent synthetics (trapezoid membership function)
Key 5* - Fuzzy geometric mean (trapezoid membership function)
Key 6* - Fuzzy extent synthetics (triangular membership function)
Key 7* - Fuzzy geometric mean (triangular membership function)

1. At the normalization phase of this work, the beneficial and non-beneficiary perspectives were considered. The minimum and maximum values for each of the parameters are 0 and 1, respectively. These are highly assigned to levels 1 and 3. However, level 2 has the unique characteristics of displaying a value between 0.5 and 0.5150.
2. The differences between the leaving and entering variables are 0.7500, 6.4183E-06 and 0.7500 for levels 1, 2 and 3, respectively. However, this is a situation where the fuzzy extent synthetic where the values of A, B and E are 287 million dollars, 2861 billions and 81750 kilotons. For parameter D, which is non-beneficial, the lower the value obtained, the better. This means that the 1.5 units of materials used predicted by Benrajesh and Rajan (2019) are better than our value of 3.5 units obtained from the fuzzy extent (triangular membership)- based hybrid model proposed by us. Notwithstanding, another viewpoint to the interpretation of the results is to associate the changes in the value of (3.5 – 1.5) 1/5, which is 133% as the improvement attained when the original value from the method was suppressed by 133%. This makes our results and model superior to Benrajesh and Rajan (2019) as it reduces the uncertainty by the same amount. Now consider the parameter F, where the value obtained by our model is 100% over the value given by Benrajesh and Rajan (2019). From one perspective, Benrajesh and Rajan (2019) may be taken as superior to our work because the parameter F being considered is non-beneficial, which means the lower its value, the more preferred it is to our method. But another perspective is that when we consider reducing the uncertainty of the decision-making given by the data, the model is effective by the measure of the differences in value, which could be of negative or positive differences. Here, the magnitude of the values is considered. Therefore, by fuzzification, our method is better than Benrajesh and Rajan (2019) by 100%.

Besides and completely varying from previous studies, three different principles of science involving the fuzzy method, the 0/1 knapsack dynamic programming and the Pareto method are combined in a unique way to differentiate the capability of the Taguchi method from the robust integrated method that tracks uncertainty monitors optimization and engage in discrimination of the parameters in the exhaust emission problem for vehicles used for the delivery of goods. In this work, multiple variations of methods were experimented upon to show a wide range of results obtained. Apart from the first case where the triangular membership function is considered, a second case where the fuzzy geometric mean displaces the fuzzy synthetic method is considered. With this new set-up, parameters A, B and E remain the same in value between our proposed method and the Taguchi method of Benrajesh and Rajan (2019) while Parameters C, D and C are different. In each of these parameters, our values, i.e. 30.34, 3.5 and 2.46 X 107 for parameters C, D and F outgrow Benrajesh and Rajan's (2019) results. The justification is that the differences are the thresholds with which our model reduces uncertainty in the evaluation. However, another perspective is that Benrajesh and Rajan

(2019) is better than our own since the parameters fall under the non-beneficial criteria and lower values, which Benrajesh and Rajan (2019) produce are desirable.

In other results such as in Tables 7C, 7D, 7E, 7F, 7G, and 7H, instead of using fuzzy extent triangular, the results of which were displayed in 7A, substitutes were made with the following: fuzzy extents synthetic (trapezoidal, Table 7C), fuzzy geometric mean (trapezoidal, Table 7D), fuzzy extent trapezoidal, Table 7E), fuzzy geometric trapezoidal, Table 7F), fuzzy extents synthetic (triangular, Table 7G), fuzzy geometric mean (triangular, Table 7H). The results obtained in all other tables, i.e. Tables 7C, 7D, 7E, 7F, 7G and 7H are similar to the previous ones discussed.

5. CONCLUSIONS

In this paper, the fuzzy-0/1-KDP-PROMETHEE (Fuzzy-0/1 Knapsack dynamic programming-Preference Ranking Organization Method for Enrichment Evaluation) approach to concurrently reduce uncertainty, optimize the capacity of the knapsack and establish the preferred option among the parameters of green logistics was proposed and tested with several variants. The results of the optimization regarding the 6 parameters used in this study are as follows: Revenue attained in the packing industry for a year is 287 million dollars, packing units sold is 2861 billion. Others are 30.34 compound annual growth rate (2015), 3.5 materials used for packing, 81750 kilo tons quantity consumed and 2.46 X 107 carbon dioxide equivalent of packing materials. The results are the same for the three methods of Fuzzy Extent Synthetic(Triangular) - 0/1 Knapsack Dynamic - PROMETHEE II, Fuzzy Geometric mean(triangular) - 0/1 Knapsack Dynamic - PROMETHEE II and Fuzzy Extent Synthetic(trapezoidal) - 0/1 Knapsack Dynamic - PROMETHEE II tested in the work.

Moreover, the study results contribute to green logistics, specifically its planning and design, regarding the movement of delivery vehicles of packed goods in cities. Bearing in mind that the literature field data used for the present study (i.e. Benrajesh and Rajan, 2019) was extracted from the Indian operating environment of delivery vehicles in the packing industry, the study results will promote emission reduction where moving products from one location to another, and few CO2 emissions will pollute the atmosphere. The results of this study, which may apply to all groups of companies, i.e. small, medium and large enterprises, will help in planning. It will assist in the development of a window of the e-logistics market where the focus will be on competitiveness and hence indirectly reduce health cost expenditure by individuals, companies and governments. The results of the study may be reproduced and deployed as background studies and information given to new companies with a heavy focus on vehicle logistic services. These companies could use this information for planning in situations where a huge fleet of vehicles for goods delivery is involved. The study's limitations include the following. First more widespread parameters should have been used instead of the six parameters used. This would have created a more robust study. Besides, a comparison of different geographical, political and commercial areas of the study country ought to have been made to make the work more acceptable to its users. The reliability of this study could also be improved if the study had been complimented with intensive questionnaire reporting from many parts of the country.

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