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Vehicle Exhausts Emission Process Parametric Optimization and Selection using the Fuzzy-Knapsack Dynamic Programming-EDAS Method for Logistics Application

Alexander Iwodi Agada[a], John Rajan[b], Swaminathan Jose[c], Sunday Ayoola Oke[a, *], Pandiaraj Benrajesh[d], Elkanah Olaosebikan Oyetunji[e], Wasiu Oyediran Adedeji[f], Kasali Aderinmoye Adedeji[e]

[a] *Department of Mechanical Engineering, University of Lagos, Lagos, 101017, Nigeria*
[b]*Department of Manufacturing Engineering, School of Mechanical Engineering, Vellore Institute of Technology, Vellore, 632014, India*
[c]*School of Mechanical Engineering, Vellore Institute of Technology, Vellore, 632014, India*
[d]*Department of Mechanical and Automobile Engineering, Christ University, Bengaluru, India*
[e] *Department of Mechanical Engineering, Lagos State University, Epe Campus, 102101, Nigeria*
[f]*Department of Mechanical Engineering, Osun State University, Osogbo, 210001, Nigeria*

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ABSTRACT

Vehicular exhaust emissions threaten health with the poisonous gas discharges attributed to health problems. Thus, there is an urgent need to reduce discharges from exhaust emissions during logistic services. Consequently, this study proposes a fuzzy (F)-0/1 knapsack dynamic programming (0/1 KDP)-EDAS method, shortened as the F-0/1KDP-EDAS method. The method minimizes the exhaust emissions from vehicles while identifying the most important parameter contributing to the emission process. Then, this study extracts the factor-level information from the process and applies the fuzzy extent and fuzzy geometric concepts in the perspectives of three decision-makers, notably the bottling manager, head of business operations and chief executive officers as evaluated by the researchers. The outcomes of both fuzzy concept applications are then integrated with the 0/1 KDP scheme to produce criteria weights that are used in the EDAS method to produce the final results. The outcome of the fuzzy synthetic method yielded 0.1621 for parameters A, B, C, E and F while parameter D was 0.8931. After applying the 0/1 KDP scheme, parameters A, C, D and F were assigned zero values indicating non-contributory characteristics to the optimization process while parameters B and E were assigned the values of 20.59 and 904.89 respectively. The integrated F-0/1KDP scheme yielded 0.0222 and 0.9778, respectively. The originality of this work is the introduction of the fuzzy-knapsack-EDAS method to control exhaust emissions from vehicles in logistic services. Policy makers and logistic managers may employ the findings reported here to revise the periodic standards set for vehicles in exhaust emissions.

1. Introduction

The goal of environmental control agencies in various countries aligns with being able to guarantee an environment of minimum or even zero environmental pollution from vehicles and other sources [1, 10, 15, 16, 18]. However, the parking industries have vehicles that ply roads and such

* Corresponding author. Tel.: +234-080-581-791-90
E-mail address: saoke01@gmail.com.

carbon-fueled engine vehicles affect the air quality of the environment through emissions from their exhausts. An important perspective to enhance environmental air quality is to optimize the exhaust emissions from these carbon-fueled engine vehicles [9]. This occurs during their logistic activities whereby they deliver packed goods to the customers [24]. The Netherlands [8] monitored the exhaust emissions from vehicles for at least 20 years (i.e. between 2000 and 2020) while the concern for enhanced quality had been shown in Italy by measurements of emissions in the country for 18 years (i.e. 1992 to 2010). This problem is even more compelling as governments in several countries experience increased health costs, which they have to subsidize for their citizens [6, 11, 27, 28]. This health problem is largely associated with emissions from vehicles, which may be the cause of breathing difficulties, eye problems and lung disorders [3, 5, 12]. Country-wide studies between emission and health effects were conducted in some countries such as China [13, 14, 22, 26, 29], and Thailand [17]. Nonetheless, in the context of a research process, it is impossible to experiment with all the associated factors of exhaust emissions from vehicles. Thus, for economic consideration, only a few of the exhaust emission parameters can be chosen for analysis and the framework of factor-level development of the Taguchi method, which can be used as a platform to study this problem is used in this work. Then the factor-level framework is combined with the fuzzy synthetic method and the fuzzy geometric method. Afterwards, the 0/1 knapsack dynamic programming idea is introduced and finally, the results are used as weights to the EDAS (evaluation based on distance from average solution) method, which is used for the final computation [19].

Moreover, extensive studies in the academic and logistics domain reveal that the emerging interest in optimizing exhaust emissions in packaging industries has been limited [2, 7]. However, the study by Benrajesh and Rajan [3], which appears as the major and representative study in this group, seems to focus on the optimal parametric determination side. It was initiated by the establishment of the key exhaust emission factors, introducing the diverse levels of these factors, and determining the signal-to-noise ratios and the average signal-to-noise ratios of these exhaust emission process parameters. More traditionally, in practice, the vehicle fleet manager has concentrated on the use of intuition, experience and suggestions by key and highly ranked and experienced team members and advisors. This traditional approach is unreliable and often fails to yield the expected results. Unfortunately, there is no mature technical outcomes with a particular interest in analyzing the combined optimal solutions and display selection preferences of exhaust emission process from the standpoint of logistics and packing industry applications. Apart from the intuition used in practice, the newly suggested solution by Benrajesh and Rajan [3] terminates discussions at the optimal parametric setting determination. To the best of the present authors' knowledge, logistics and exhaust emission process from the standpoint of combined optimization and selection have not been considered in the relevant literature. However, only optimization studies have been made in the literature. Notwithstanding literature search suggests that 0/1 knapsack is being used to optimize processes characterized by weights and values, which is associated with logistic vehicles and products being packed and delivered in the logistic process.

Also, the EDAS method has gained popularity for its success in engineering and logistic practice and analysis [19]. Admittedly, while Benrajesh and Rajan [3] limited their explorations to the Taguchi application alone, consideration of the robust choice and optimization attribute of the 0/1 knapsack dynamic programming scheme has been ignored. Further, the interactive features of the EDAS framework incorporating the factors using some special elements to distinguish beneficial from non-beneficial parameters and subsequently classify parameters according to the order of importance is also ignored in previous studies [3, 19]. Besides, there is a potential interaction omitted previously among Taguchi's method elements of delta values and optimal parametric settings, the identified optimal values in a streamlined manner from the 0/1 knapsack dynamic programming method and their use as weight criteria for the EDAS method. This interaction should be exploited. Therefore an integrated method is proposed in this article to consist of the fuzzy method, 0/1 knapsack dynamic programming method and the EDAS method. It is aimed to match the need of the packing industry in an attempt to lower exhaust emissions from vehicles used in transporting goods from one part of the country to another. Thus, the work solves the problem of exhaust emission reduction. The principal contributions of this article are as follows:

In the first instance, the 0/1 knapsack dynamic programming is contemplated and the utility of this programme is to discriminate at first among all the parameters of the exhaust emission process and concentrate on optimizing them by deploying a mechanism which attains a maximum value obtainable. This is done by selecting items such that the sum of the weights does not exceed the knapsack capacity. Secondly, a new optimization-based selection method developed to compare the fuzzy method, 0/1 knapsack dynamic programming method and the EDAS method (F-0/1KDP-EDAS) to minimize exhaust emission from vehicles and choose the best parameter for planning has been proposed for planning purposes.

In this study, the structure of the paper organization is as follows. First, the introduction considers the environmental effects and famous programmes used to solve these problems and the countries interested in these issues. It declares why the problem discussed is important. Next, the literature review is presented on the existing knowledge on the topic. This presentation allows us to understand the research gap and justifies the need for the present study. Following this, the methodology for the development of the method is presented. Then, the results and discussion section is provided. The paper concludes in the last section with remarks. It also includes limitations and future studies on the subject.

2. Literature review

Research on green logistics has long shown evidence of extensive investigations over the past few years. For instance, Bennani et al. [4] proposed a hybrid F-SWARA and F-ENTROPY to optimise the weights of location criteria in the neighbourhood of the green logistics framework. The emphasis of the article is how the system behaves in a fuzzy situation. However, their approach excludes the minimization of experimental costs. But the experimental cost to obtain data for method verification could be prohibitively high. In turn, Eslamipoor [12] employed a two-stage stochastic model to locate product collection centres focusing on environmental parameters and risks. The method is a mixture of a mixed integer programming model and fuzziness. The drawback of the work relative to the present study is the absence of a mechanism to differentiate the composite parameters one from another regarding importance. On the other hand, some other authors have integrated multicriteria prioritization methods with optimisation methods (i.e. TOPSIS and Taguchi method) to overcome this difficulty.

Atmayudha et al. [2] proposed two optimisation methods of multi-objective optimisation and single-objective optimisation to minimise the objectives of logistics cost and CO_2 emissions (for multi-objective optimisation) and to only minimize only one of the objectives (for single-objective optimisation). The drawback of the approach remains the absence of a prioritization scheme despite the optimisation success of the method. Prioritized parameters are essential to determine points where emphasis is required. Moreover, Stekelorum et al. [23] deployed a fuzzy-set method to understand how diverse groupings of internal and external green supply chain management activities impact third-party logistics accomplishments. The new method of analyzing the problem was considered effective.

As regards empirical methods in green logistics, Karaman et al. [16] applied the signalling theory to capture the association between sustainability reporting and green logistics performance. Roughly, data were obtained for 117 countries over 10-year coverage. The outcome of this research showcased how each dimension of the logistics performance index could be enhanced regarding sustainability enhancement. Liu and Ma [18] applied the Internet of Things technology to boast green logistics management as well as supply chain system construction. Sun and Li [25] deployed an evolutionary equilibrium stability analysis to analyze green logistics packaging and specifically recyclable systems. They focused on the behavioural choice of governments, consumers and enterprises.

Maji et al. [20] analyzed green logistics efforts and their influence on environmental sustainability in a Nigerian city using a stratified snowball sampling method, chi-square, descriptive statistics and the regression method. It was declared that 2/3 of logistics managers could appreciate the influence of the negative aspects on the environment and merely 20% promoted green logistics efforts. However, the drawback of the work is the poor treatment of vehicle exhaust emission on a large scale in the article despite its significant importance.

Furthermore, Vo and Nguyen [27] provided empirical justification for the drive towards green logistics activities and environmental accomplishment. The evidence was on 142 logistics managers in Vietnam using partial least squares structural equation modelling. A major result is that a strong positive correlation exists between green logistics management practices and green logistics performance and the study supports a natural resource-based view. However, a strong weakness of the study is the absence of information on the moderating role of exhaust emission control on the overall picture of the subject. Besides, Ngo [21] provided empirical evidence on the Vietnamese SMEs by focusing on the logistics industries by emphasizing green market orientation and how it could be adopted. The balanced score method was adopted and the results revealed that the adoption of green market orientation in 338 small and medium enterprises should be an indirect enhancement in the operational performance of the enterprises. Notwithstanding, the work has the drawback of an absence of thoughts on the optimisation of practices. Furthermore, in a related study to the present one, an Indian automotive organization was examined regarding green logistics practices [5]. The emphasis was an analysis of green practice options using the analytics hierarchy process. It was concluded that a clinch joint is the likely essential option for assembly activities. But the best option for the packaging industry was carbon-positive packaging material.

Table 1 provides an impression of the attributes of the selected publication previously published in the green logistics literature. The contributions made by various scholars are presented in tabular form to reveal the significance of the present study. Green logistics as discussed in the present study focused on the totality of business practices, which reduces the environmental influence of emissions from the exhaust pipes of vehicles. In reality, three principal gases, namely nitrogen oxides (NO_x), carbon monoxide (CO) and carbon dioxide (CO_2) are unwanted emissions from vehicles. While CO, regarded as an indivisible gas, which emerges from the fuel's incomplete combustion is rated as highly toxic and unfriendly to humans, the CO_2 is known for its threat to climate change being a greenhouse gas. However, NO_x is common in all combustion processes. Therefore, at a glance, these important attributes of previous studies reveal the gap that is opened for the present study to cover. It is worth emphasizing here that the present study, which promotes sustainable logistics, is such an acceptable bottom line while maintaining customer satisfaction regarding delivery time and quality of delivered products. But the well-being of the planet is also considered. In Table 1, the parameters of the various studies are summarized for use in the statistical analysis of their frequency of occurrence in previous studies. To our knowledge, these parameters are hardly repeated in many studies as each study portrays a new dimension of analysis. It points out that the area of study is still in its infancy hence there is no overlap of parametric studies. In comparing the few published articles stated in Table 1, there exist some gaps within the literature. Prominent in the gap is that the majority of methods exclude fuzzy extent analysis and fuzzy geometric means method despite claims by some authors to have reduced uncertainty. Although commendable to have tackled the uncertain influence on green supply chain and logistics, Stekelorum et al. [23] seem to be the only proponent of fuzzy doctrine but the above-mentioned fuzzy types were not considered in the literature. Secondly, there exist gaps concerning the 0/1 knapsack dynamic Programme, which had not been tackled or deployed in the green logistic literature. The third gap is the absence of the EDAS method in the literature.

Table 1: Literature review studies associated with green logistics in packing industries

S/N	Author(s)	Study type	Prominent parameters	Applications	Mathematical tools	Findings
1	Stekelorum et al. [23]	Modelling and empirical	Eco-design, packaging, warehousing, greenness, performance, reverse logistics, distribution strategies, transportation, cooperation with customers	Third-party logistics providers	Fuzzy set	Fuzzy set is new in attaining internal and external constructs
2	Atmayudha et al. [2]	Modelling	Charter cost, fuel cost, number of rounds–trip, crude oil throughput	Crude oil logistics and transportation	Optimization methods with single and multiple objectives structures	Minimization of logistic costs and CO_2 emissions may be attained by using LNG-fueled ships.
3	Eslamipoor [12]	Modelling	Fixed location, factory production, product rates, recycling cost, emission cost, fixed, transportation and depo capacity costs	Pharmaceutical holding company	Two-stage Stochastic model	Uncertainty influences customer demand and product rate return
4	Bennani et al. [4]	Modelling	Economic, social, environmental, and territorial criteria	Green logistics platforms	Hybrid F-SWARA and F-ENTROPY	Fuzzified green logistics structures have been established
5	Krstić et al. [17]	Modelling	Technological economic, social, political, service quality, and environmental criteria	Industry 4.0 technologies, Logistics	Delphi, analytical network process and comprehensive distance-based ranking methods, fuzzy	Industry 4.0 technologies fails to guarantee an acceptable growth scenario within the model

				providers		
6	Sureeyatanapas et al. [24]	Empirical	Company characteristics, number of respondents	Logistics service provider	Manufacturing	Factors impacting the adoption of green logistics include pressure from customers, financial status among others
7	Ngo [21]	Empirical and model	Respondents' characteristics, Frequency, Percentage, Cronbach's Alpha and composite reliability	Logistics industry, SME's	SMEs	Structural equation modelling and partial least squares
8	Cui et al. [7]	Empirical	Logistics volumes, GHG emission factors and logistics transportation features	Logistics transportation	Multi-source big data scheme	Gross domestic product and driving speed principally drive GHG exhaust.
9	Vo and Nguyen [27]	Empirical	Previous year's revenue, age and firm size,	Vietnamese logistics businesses	Partial least squares, structural equation modelling	Positive association exists between green intellectual capital and green logistics management practices
10	Maji et al. [20]	Empirical	Green logistics construct items	Logistics management	Descriptive statistics, chi-square and regression	Logistics categories impact logistics practices, Logistics managers' experience influences companies' sustainable compliance
11	Liu and Ma [18]	Empirical	Vehicle emission reduction, the accuracy of information circulation, cost reduction	Logistics companies	Reliability assessment strategy	Work efficiency enhances based on green logistics and Internet of things
12	de Souza et al. [8]	Modelling	Indicators metrics associated with purchase, recycling, packing, reuse and energy	Plastic sector	Analytic hierarchy process	Green logistics is close to managers through metrics for various sectors

3. Methodology

The research report of Benrajesh and Rajan [3] stimulated the present study for different reasons. First, it appears as the first quantitative study to adopt the design of experiments approach to promote green logistics in the packing industry. Since it is economical, it is encouraging to adopt the orthogonal array framework, which is the basis of the economics of experimentation while conducting a large-scale study such as the present one, particularly in an economic-conscious operating environment brought about by dwindling company fortunes globally. Severally, although data are available in operations, it is difficult to obtain exactly similar data in the same environment due to differences in perceptions of the research and the frameworks set for the different studies. Hence, it may be challenging to have a platform to compare the results of the F-0/1 KDP-EDAS method proposed in the present study. Consequently, it makes sense to consult Benrajesh and Rajan [3] as secondary data to attain the comparison aim of the present study. Moreover, we extend Benrajesh and Rajan [3] by resting on the factor-level framework, to produce the orthogonal array which contributes to the interface with the 0/1 knapsack dynamic programming method. In this study, the same six factors used in Benrajesh and Rajan [3] were adopted in the present work. The motivation for using the same factors is to facilitate a comparison between the responses given by the Taguchi method, which ignores uncertainty and the fuzzy-based multicriteria method which reduces uncertainty. Moreover, at the commencement of this research, it is not known if any of the six factors is weak to influence the results. Hence, no factor was omitted from those declared in Benrajesh and Rajan [3]. Thus, gathering data on the design becomes the first phase of the discussion of the F-0/1 KDP-EDAS method. We analyze the orthogonal array as a 6 x 3 factor-level configuration, which eases the conversion of the data to a normalized form.

Two forms of fuzzy methods such as the fuzzy extent synthetic and fuzzy geometric means are introduced. The output of the fuzzy method is the second phase of the F-0/1 KDP-EDAS method, which serves as an input to the fourth phase of the method. Notice that the third phase method is the computation of the 0/1 KDP. The outcome of the normalization is fuzed with the 0/1 KDP method. The mechanism of the 0/1 KDP method aids in discriminating among parameters; it separates the most sensitive from the least sensitive ones. The application of this mechanism is part of the goal of the present study. With the discriminated parameters identified, the several phases of the F-0/1 KDP-EDAS method are completed. Thirdly, the EDAS is adopted by introducing the multicriteria weights from the combination of the 0/1 KDP method and the orthogonal array method into the EDAS structure

[19], and the final ranks of the parameters are delivered. This is the final phase of the study.

3.1 The 0/1 knapsack problem

In the exhaust emission optimization and selection problem, three distinct problem formulations are combined to form the problem, which are the fuzzy problem aspect, the 0/1 knapsack problem and the EDAS problem. The 0/1 knapsack problem with the exhaust emission, which could hardly be found to be explained in the literature, is discussed here in its relevance to the exhaust emission perspective. By exploring the 0/1 knapsack problem, it is understood that there are six parameters A, B, C, D, E and F. These parameters, which are extracted from Benrajesh and Rajan [3] are assumed to be objects. Thus there are six objects considered in this problem. For each parameter, there are three distinct levels available. Now we introduce the capacity of the system regarding the limits which the system cannot exceed. This is often stated as a common value such as 6, which is used in the present problem. This is usually obtained after the normalization of all the parametric values and in this case, the values are normalized between 2 and 6. The method is that the parameters, which are objects are to be used to fill a particular bag. But to fill the bag up with the parameters, the capacity, which is to be given i.e. 7 is known but the total weight at the initial level may exceed the 7 being considered as the total weight. It means that all the parameters cannot be fitted into the bag at the same time. To solve this problem, the researcher needs to consider only the subset of the parameters and their values. The remaining has to be carried out of the bag, which means that it is not needed. Thus, since we are considering emissions, the bag used for analogy needs to be filled up such that the total emission values from the exhaust considered to fill the bag are minimum. Here emissions are not desired. The solution to the exhaust emission problem needs to be given in the form of a set containing 0 and 1 such as x = {0, 1, 0, 1, 1, 1}, which is a set containing six parameters A, B, C, D, E and F with each represented by either 0 or 1. A value of 0 means that the parameter is not included in the result while 1 means that the parameter is included for further processing. In the case discussed, with an example of x containing six elements, parameters A, D, E and F are included in the exhaust emission on the optimization bag while parameters A and C are not the included set members. Here fractions are not permitted but 0 and 1 only. This means that the weights that the system carries are not divisible. The interpretation for emission fumes is a group of emission fumes at a time. It means as fumes come out, the researcher cannot take a fraction of the batch of fumes emitted from the exhaust pipes of vehicles in the packing industry. This means that as the parameters are indivisible, it is either it is considered or not. In sum, the author needs to carry the objects (parameters) such that the sum of the emissions and x_i is minimized. Also the sum of the weights multiplied by x_i such as less or equal to the capacity introduced into the bag.

Furthermore, the 0/1 knapsack dynamic programming method is applied to the exhaust emission control problem to find a way in optimizing and enhancing the process. This means that Table 1 of Benrajesh and Rajan [3] needs to be interpreted and the problem formulated for the 0/1 knapsack dynamic programming framework. By taking a close look at the controlled factors (parameters) of Table 1 in Benrajesh and Rajan [3], we will be focusing on two input parameters, which are the most input to emission control with information on weights and costs. The information based on cost is according to the packing units sold and the weight is based on the quantity consumed in kilotons. The values for these two parameters are extracted into two columns of v denoting packaging units sold and wt the weight of quantity consumed in kilotons. After careful consideration of the magnitude of values collected, we opted the downscale the values to digits between 2 and 6 using Microsoft Excel in computing a normalizing procedure for the problem. To normalize, Equation (1) is used:

$$X_{new} = ((b-a)\ (X-y)(Z-y)) + a \qquad (1)$$

where a is the minimum row or column value
b is the maximum row or column value

During the procedure to normalize the values, in place of (X-y)/(Z-y), we used $X_{intermediate}$, which was derived from the Xnew equation. Then the equation of X_{new} is given as Equation (2)

$$X_{new} = (X_{ij} - X_{min})/(X_{max} - X_{min}) \qquad (2)$$

3.2 The proposed fuzzy 0/1 knapsack-EDAS method

To apply the fuzzy method to the exhaust emission problem, the following steps were followed:

Step 1: Obtain the factors (parameters) and their levels from the field data obtained.

Step 2: Decide on the fuzzy approach to use: There are two main fuzzy types used in the present study, which are mainly the fuzzy extent synthetic and fuzzy geometric mean method. The steps for both techniques are similar in the present study.

Step 3: Decide on the decision makers to adapt by their number and their levels in the hierarchy. A particular case of a bottling plant is adopted and emphasis is placed on the packing process. In this instance, the three relevant business decision-makers in the packaging industry part of the business are the business manager (BM), the head of business operations (HBO) and the chief executive officer (CEO).

Step 4: Establish the linguistic types and the number of entities in the linguistic classification. In this case, seven distinct linguistic types govern the evaluations made in this work according to the fuzzy extent of synthetic and fuzzy geometric methods. The linguistic terms are extremely low (EL), very low (VL), low(L), medium(M), high(H), very high(VH) and extremely high(EH). Denote each linguistic term by a fuzzy number, which has the lower, middle and upper parts and this could be guided by the lower boundary of 0 and the upper boundary of 1 while the middle team is in-between.

Step 5: Conduct the decision maker's evaluation process by placing each parameter against the decision maker's evaluation in the contexts of the fuzzy extent and fuzzy geometric means analysis.

Step 6: Compute the 0/1 knapsack procedure. There are two approaches to this procedure. The dynamic programming and the set theory approach. However, for the present study, the dynamic programming approach is used for this study. The following process for the dynamic programming process scheme is involved.

Step 6.1: Consider the parameters as objects for the exhaust emission problem. Also, for each object, attach a criterion such as the measure of emission, which is to be minimized. Also imagine that a bag (say a balloon that could contain air) is to be filled with the quantum of emitted gasses from the vehicles, which are treated in batches. Each quantum has weight. There is also a maximum weight to be filled by the bag (balloon). Define the specific value of this weight.

Step 6.2: The intention is to fill the balloon(bag) with the emission from exhaust (gas). Considering the object, all the objects (parameters) cannot fill the balloon with gases (emissions) at the same time because of the capacity of the emissions. Thus, a few weights of the parameters may have to be carried by the balloon. This is the subset of the objects. The objects (parameters) need to fill the balloon with gases (emissions) such that the total pollution due to the emissions is minimum. The solution needs to be presented in the form of a set such that the components of the set have 0 and 1 entries. This means that the objects that I will carry are not divisible, which means that a fraction of the object cannot be obtained, it means that the emissions do not split.

Step 6.3: Solve the problem in a sequence of decisions. it means that you consider the elements of the set of parameters. Decide whether you should include each or not. Usually, you start from the last object towards the first object.

Step 6.4: Try all possible solutions and pick up the best one. Consider a set with four objects. The possible solutions may be 0000,1111,1001,1000 and 1100. Here, 0 means not included while 1 means included. Here, you will try all these five options and pick up the best one from the analysis. In this example, the total number of solutions possible is 2^4, which is 16 possible solutions. To generalize it, far objects, you could for 2^n solutions. To try all the possible solutions, it is time-consuming and a shorter method should be used. The easy approach to obtaining this is dynamic programming. The problem is then solved using the tabulation method where values are fitted into the table to obtain a solution for the problem.

Step 6.5: Consider the table and start with the zero capacity of the bag while you consider the available weight if the object can enter the bag.

Step 6.6: Consider the first row and this is the initial level where we will not consider any object. The fill "0" throughout the first row is the emissions. Also along the capacity column of 0, fill "0" throughout.

Step 6.7: Consider the first object and take the next row while ignoring the remaining. Do the evaluation.

Step 6.8: Continue the evaluation until the end of the allocation. Do this until you reach the I^th row where all the objects are considered.

Step 7: Conduct the EDAS method

Step 7.1: Determine the average solution (AV), Equation (3)

$$AV_j = \frac{\sum_{i=n}^{n} X_{ij}}{n} \qquad (3)$$

Where X_{ij} is the value for an input parameter and n is the number of alternatives for the parameter. For example, the revenue generated may be 52 million dollars, 171 million dollars and 287 million dollars for each level of the input parameters. For this case scenario, X_{ij} is 52 million for level 1, 171 million for level 2 and 287 million for level 3. However, n is 3 representing the number of levels 1, 2 and 3.

Step 7.2: Calculate the positive distance from the average (PDA)

If the j^{th} criterion is beneficial, then Equation (4):

$$PDA_{ij} = \frac{\max(0, X_{ij} - AV_{ij})}{AV_{ij}} \qquad (4)$$

Where X_{ij} is as defined in Equation (3). AV_{ij} is also stated in Equation (3)

If the j^{th} criterion is non-beneficial, then Equation (5):

$$PDA_{ij} = \frac{\max(0, AV_{ij} - X_{ij})}{AV_{ij}} \qquad (5)$$

Where X_{ij} is as defined in Equation (1). AV_{ij} is also stated in Equation (1)

Step 7.3: Calculate the negative distance from the average (NDA)

If the j^{th} criterion is beneficial

Beneficial parameters are those that will be improved upon or increased. Then compute Equation (6):

$$NDA_{ij} = \frac{\max(0, AV_{ij} - X_{ij})}{AV_{ij}} \qquad (6)$$

Where X_{ij} is also as defined in Equation (3). AV_{ij} is also stated in Equation (3)

If the j^{th} criterion is non-beneficial

Non-beneficial parameters are those which we aim to reduce their values or minimize. Then compute using Equation (7):

$$NDA_{ij} = \frac{\max(0, X_{ij} - AV_{ij})}{AV_{ij}} \qquad (7)$$

Where X_{ij} has also been defined in Equation (3). AV_{ij} is also stated in Equation (3)

Step 7.4: Calculate the weighted sum from PDA, Equation (8)

$$SP_i = \sum_{i=1}^{n} w_i PDA_{ij} \qquad (8)$$

Where w_i is the weighted value

Step 7.5: Calculate the weighted sum from NDA, Equation (9)

$$SN_i = \sum_{i=1}^{n} w_i NDA_{ij} \qquad (9)$$

Also, w_i is the weighted value

Step 7.6: Calculate the normalized values of SP and SN

Step 7.7: Normalize the values of NSP and NSN, Equations (10) and (11):

$$NSP_i = \frac{SP_i}{\max_i (SP_i)} \qquad (10)$$

$$NSN_i = 1 - \frac{SN_i}{\max_i (SN_i)} \qquad (11)$$

Where $\max_i$ is the maximum value of the i^{th} item, Equation (12)

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \qquad (12)$$

Where AS_i is the average sum of normalized values for NSP and NSN

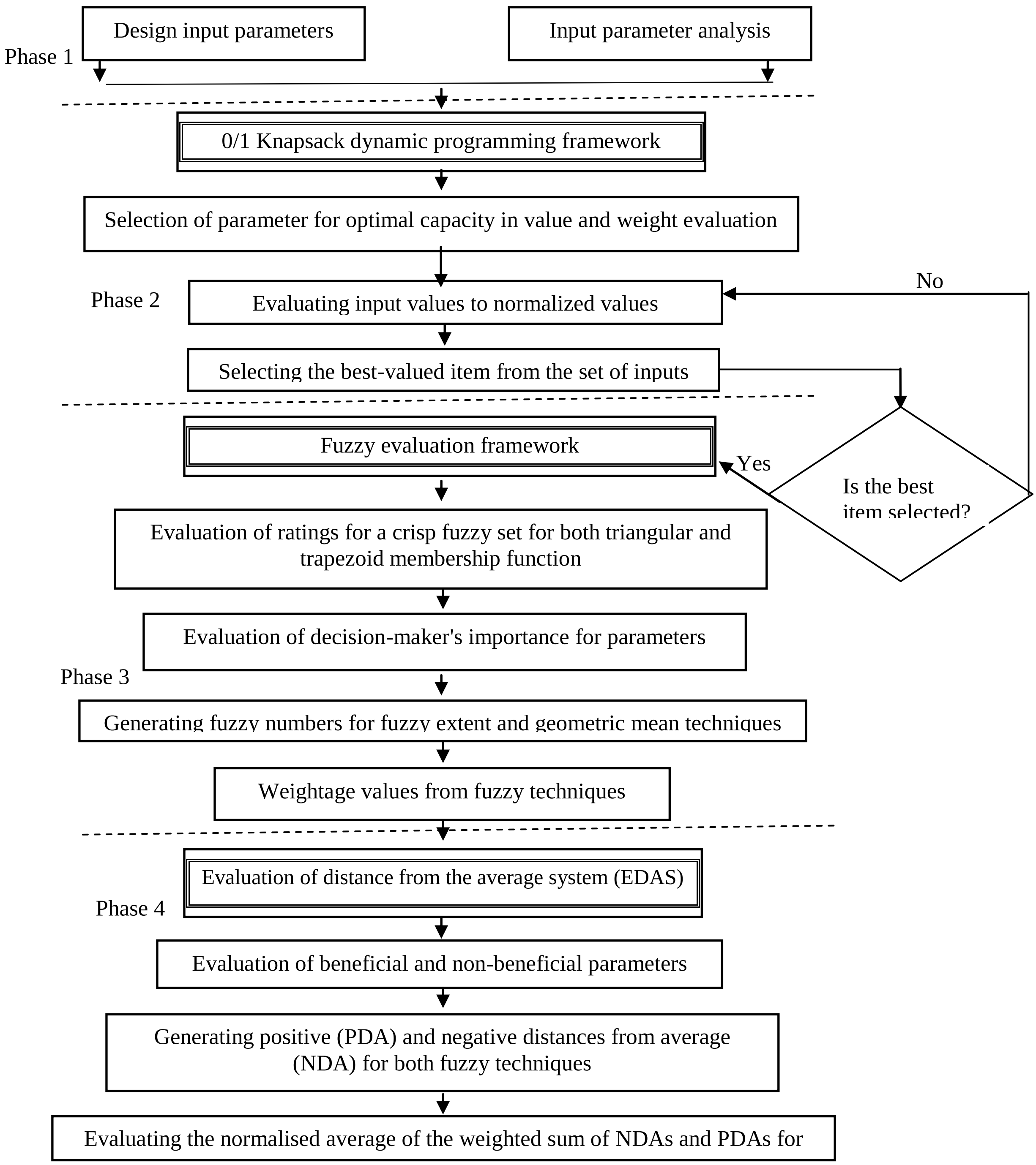

Figure 1. Flowchart on fuzzy– 0/1 knapsack–EDAS method

4. Results and discussion

We obtained the following pairs of values for the respective descriptions of values of packing units sold and quantity consumed per kiloton. These are 127 and 5581 for the first set, 1494 and 4336 for the second set and 2861 and 81750 for the third set. These mentioned values were extracted from Table 1 of Benrajesh and Rajan [3]. However, to apply the 0/1 knapsack dynamic programming (0/1 KDP) method, we aim at attaining a maximum value obtainable by selecting a subject of items such that the sum of the weights does not exceed a certain capacity (i.e. the knapsack capacity). Rows in Table 1 created by us denoted a set of items with weights and monetary value. The columns hold knapsack capacity limits.

Thus considering the first item in Table 1, it is assumed to pick the first row having zero weight and zero monetary value. This is a stage where the knapsack is considered not to exist at all without capacity or form. For us to use a knapsack programme, we begin with the least possible capacity which is either 0 or 1. Moreover, to achieve or figure out the best possible values from each capacity, the second item receives the information from the first row to formulate a combined best value for the items on the first two rows. This process continues for the third and fourth items. For each column, we consider either including or not the current item, which brings about the 0 and 1 in knapsack programming. If we do not include the current item then we look one row above. But if we do include the current item then we look one row above still although shifted over to the left by the weight of the current item. Because that will be the state will the best possible value to enter the knapsack large enough to hold it. In the end, we get the best we can achieve in the Table's last cell. But which one do we need to select? The last value on the row of items from Table 1 and the row above has to differ in size to be selected. Since the value is above, it has to be subtracted by the weights of the selected item to reduce the value to a considerably smaller knapsack. Repeat the technique until you get to zero. Given the above description, we will illustrate the working procedure of the knapsack with the emission data obtained from Benrajesh and Rajan [3]. Notice that the value in Pairs 127 and 5581, 1494 and 4336, and 2861 and 81750 have been translated into normalized values set between 2 and 6 for convenience in computations. Therefore, the respective values of 127 and 5581 yielded 2 and 6, while 1494 and 4336 also yielded 2 and 6 while also 2861 and 81750 yielded 2 and 6. The identical values are the result of the very limited value considered. The effect of converting these values to normalized form would have been revealed if we had several rows of data. We now set this data as Table 1. The first two columns of Table 1 and with the headings of v and wt indicate the value for the packing units sold and the weight for the quantity consumed, respectively. The third to the ninth columns indicate the knapsack capacity limit, in which 6 is the projected capacity limit in this illustration. It means that the values of 0, 1, 2, 3, 4, 5 and 6 will be entered in the third to the ninth columns of Table 1, which is on the same as v and wt. The second row with values 0 in the first two columns is the first item considering the minimum or the least possible values. Now, commencing with column 3, row 2, we have zero 0, which is a result of an empty knapsack capacity. Column 4, row 2 is a result of a limit capacity of 1, which cannot hold weight without the value of the item. Thus, a value of zero is allocated to column 4 row 2. The remaining columns for row 2 are allocated zero as the maximum value of the item with zero weight values. Now, moving to row 3, column 3, is allocated zero because the knapsack capacity of column 3 is zero and cannot hold any value. These zeros are replicated in the whole column three (i.e. column 3, row 3; column 3, row 4; column 3, rows 5). The next step is to go to column 4 row 3. It is allocated zero because the capacity for the column is less than the weight of row 3 values. That is we cannot select row 3. By following the steps given earlier, since we are not selecting the row 3 item, we bring the value of column 4 row 2. That is we look at the row above and pick its value to allocate to row 3 column 4. These zeros at row 3 columns 5 to 8 are allocated based on the same fact that the row 3 item has a higher weight value than the knapsack limit capacity. The same applies to row 4, columns 4 to 8 and row 5, columns 4 to 8. Then back to row 3, column 9, since the limit capacity equals the item weight, item 2 will be selected. Notice that there is rules that if we do not include the current item then we look at one row above although shifted over to the left by the weight value of the current item. Based on column 9, row 3, the maximum attainable value is (2+0) (where 0 is obtained by looking at the row above and moving left in six places), the value of the row above in column 9, row 3. The maximum attainable value for column 9, row 3 is 2. The value is replicated to column 9 rows 4 and 5 considering the given explanation. Then we move to the next phase, which is to identify the item to select. From the last result in column 9, rows 5, we realize that the row above does not differ in values based on the earlier row (i.e. the last value on the row of items and the row above have to differ in size to be selected. If not, it should not be selected. If row 5 cannot be selected, we then move to row 4 since the value above does not differ, the earlier stated row is still executed, which takes us to row 3 column 9. Since the above differs in value item 2, which is row 3 will be selected. Then to get the maximum value of the knapsack capacity, we look at the row above and move six steps to the left to get to column 3 row 2. The process of selecting an item continues until you attain zero after moving to the left of the table.

Considering 0/1 knapsack programming, item 2 row 3 is selected as the best value to contain or optimize the knapsack capacity limit of 6. This item is the value for level 1 i.e. packing units sold and quantity of materials consumed in kilotons i.e. 127 and 5581.

After obtaining the optimal parameters as parameters B and F from 0/1 knapsack dynamic programming (0/1 KDP), we further investigated using a fuzzy analytical hierarchy process for weight calculation where we calculated the subjective evaluation of our input parameters by some decision-makers on the importance of weights. This was made possible by the use of a fuzzy triangular membership function to generate a fuzzified pairwise comparative matrix. The fuzzified decision makers' subjective evaluation resulted in Table 2.

Table 2. Decision makers versus linguistic terms

	Decision makers		
Parameters	BM	HBO	CEO
A	M	H	EH
B	H	VH	EH
C	L	M	EH
D	H	M	L
E	H	L	VL
F	EH	EH	EH

Table 2 encompasses the decision makers in columns 2, 3 and 4, entitled BM, HBO and CEO, which are the short forms of Business Manager, Head of Business Operations and Chief Executive Officer, respectively. These functions were selected from a packaging plant with a general structure of most packing plants in process industries obtainable globally. Notice that the six parameters, which were noticed in the field study of Benrajesh and Rajan [3] were further confirmed as realistic in a single enquiry from the officers responsible. The reliance on these factors was also because the author works in the organization and interacts extensively with the officers mentioned. The columns of Table 2 relative to the rows contain six input parameters obtained from Benrajesh and Rajan [3]. These input parameters are A, B, C, D, E and F, which represent revenue attained in packing industries for the year 2015, packing units sold, compound annual growth rate, materials used for packing, quantities consumed in kilotons and carbon dioxide equivalent of packing materials, respectively. Table 3 shows the combination of the parameters and the rating given by each decision maker, notably the Business Manager (BM), Head of Business Operations (HBO), and the Chief Executive Officer (CEO) as evaluated. The evaluation was suggested by the present authors. The credibility of the evaluation lies in that one of the authors presently engages in the service of the packing industry. Hence, he understands the perspectives of these mentioned decision-makers.

Table 3. Importance rating

Categories →		170	1494	15.70
Extremely low	EL	0	0	0.1
Very low	VL	0	0.1	0.3
Low	L	0.1	0.3	0.5
Medium	M	0.3	0.5	0.7
High	H	0.5	0.7	0.9
Very high	VH	0.7	0.9	1
Extremely high	EH	0.9	1	1

To obtain Table 3, the author then acted as if he was in any of these functions to estimate the values ascertained by these officials. Based on the estimation of the decision makers, a product could be judged in any of these importance ratings: extremely low (EL), very low (VL), low (L), medium (M), high (H), very high (VH) and extremely high (EH). Then the author proceeded to assign three important items to make a scale at the same time for each parameter. Each of these scales forms the fuzzy numbers thus representing EL with the fuzzy number (0 0 0.1), VL by (0 0.1 0.3), L by (0.1 0.3 0.5), M by (0.3 0.5 0.7), H by (0.5 0.7 0.9), VH by (0.7 0.9 1) and EH by (0.9 1 1). The assessment of the fuzzy terms of parameters A, B, C, D, E and F are (M H EH) (H VH EH), (L M EH), (H M L), (H L VL) and (EH EH EH) respectively. Now, by substituting the fuzzy terms with fuzzy numbers for each parameter, there exist three fuzzy numbers for each parameter. For example, consider parameter A with the terms (M H EH), these terms are replaced with fuzzy numbers as (0.3 0.5 0.7, 0.5 0.7 0.9, 0.9 1 1). Also, note that fuzzy extent and fuzzy geometric numbers are to be concurrently computed. To obtain the fuzzy extent values, each of the lower terms (bounds) for the fuzzy numbers is first added. This is 0.3 + 0.5 + 0.9, which gives 1.7. The middle terms of the fuzzy numbers are also added. We also have 0.5+0.7+1 for parameter A to yield 2.2. Furthermore, the upper term of the fuzzy numbers representing BM, HBO and CEO for parameter A is 0.7 + 0.9 + 1 which is 2.6. The other values are computed likewise and Table 4 is obtained.

Table 4: Decision makers' evaluation of crisp numbers

	BM			HBO			CEO			Fuzzy extent		
A	0.3	0.5	0.7	0.5	0.7	0.9	0.9	1	1	1.7	2.2	2.6
B	0.5	0.7	0.9	0.7	0.9	1	0.9	1	1	2.1	2.6	2.9
C	0.1	0.3	0.5	0.3	0.5	0.7	0.9	1	1	1.3	1.8	2.2
D	0.5	0.7	0.9	0.3	0.5	0.7	0.1	0.3	0.5	0.9	1.5	2.1
E	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9	1	1.3	1.9	2.4
F	0.9	1	1	0.9	1	1	0.9	1	1	2.7	3	3
										10	13	15.2

Notice that from the formula of the fuzzy extent method, concerning i[th] alternative, it is denoted as S_i, which is equal to Equation (13) [29].

$$S_i = \sum_{i=1}^{n} \overline{a_{ij}} \left[\sum_{i=1}^{n} \sum_{j=1}^{n} \overline{a_{ij}} \right]^{-1} \tag{13}$$

Where S_i is a measure of the fuzzy synthetic extent for the i^{th} alternative

It was noted that S_i is equal to the summation of the i^{th} item, regarding any of the parameters. This is multiplied by the reciprocal of the summation of that i^{th} item. But now, we have obtained the summation of each of the fuzzy extent numbers, the reciprocal of the summation of the fuzzy extent number gives us an invented arrangement of the summation of fuzzy numbers. For example, the summation of the lower bound numbers i.e. 1.7, 2.1, 1.3, 0.9, 1.3 and 2.7 is 10. Then the reciprocal of 10 is 0.1. This is replicated in the medium and higher bound numbers to obtain 0.0769 and 0.0658, respectively. Then, to obtain the S_i values, we multiply each of the fuzzy extents bound by the reciprocal of the summations. To demonstrate with an example, consider parameter A having a lower bound in the fuzzy extent table as 1.7. This is multiplied by the reciprocal of the summation i.e. 0.0659 to obtain 0.1118. The same process is replicated for the median number and the upper bound number to obtain 0.1692 and 0.26 respectively. Notice that 0.1184, 0.1692 and 0.26 are called the fuzzy extent weight of parameter A. This procedure of weight generation should be repeated for parameters B, C, D, E and F. The next stage is to calculate the degree of fuzzy extent weight, subject to the formula

$M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$

This also includes the formula:

$V(m_2 > m_1) = \sup_{y \geq x} [\min(Mm_1(x), Mm_2(y)]$

$= hgt\ (M_1\ M_2) = MM_2(d)$

$$\begin{matrix} 1, \text{ if } m_2 \geq m_1 \\ 0, \text{ if } u \geq u_2 \\ \dfrac{l_1 - u_2, \text{ otherwise}}{(m_2 - u_2) - (m_1 - u_1)} \end{matrix}$$

The conditions for hg_o are 1, 0 and otherwise.

The degrees of criteria are

$V(S_1 \geq S_2)$

$V(S_1 \geq S_3)$

$V(S_2 \geq S_1)$

$V(S_2 \geq S_3)$

$V(S_3 \geq S_1)$

$V(S_3 \geq S_2)$

By following the criteria stated above, Table 5 is obtained.

Table 5. Possibility for convex fuzzy

A>B	1.2088	B>A	1	C>A	1.2141	D>A	1.3664	E>A		F>A	1
A>C	1	B>C	1	C>B	1.4305	D>B	1.5789	E>B		F>B	1
A>D	1	B>D	1	C>D	1	D>C	1.1676	E>C	1	F>C	1
A>E	1	B>E	1	C>E	1.0524	D>E	1.2051	E>D	1	F>D	1
A>F	1.4860	B>F	1	C>F	1.7556	D>F	1.9201	E>F		F>E	1
VA	1	VB	1	VC	1	VD	1.1676	VE	1	VF	1
NVs	0.1621		0.1621		0.1621		0.1893		0.1621		0.1621
									0.1935		5.1676
											0.1935
					6.1676						

In Table 5, we need to compare each parameter against one another where A is compared with B, C, D, E and F respectively. Also, B is compared with A, C, D, E and F. Furthermore, C is compared with A, B, D, E and F, next, D is compared with A, B, C, E and F. Also E is compared with A, B, C, D and F. Lastly, F is compared with A, B, C, D and E. Now by starting with the first set of comparisons i.e. A with each B, C, D, E and F, the following results are obtained. By obeying the conditions, if the median number for parameter A is greater than the median number for parameter B, then the result should be 1.

However, if the lower bound number of parameter B is greater than the upper bound number of parameter A, then we write 0 as the result. Otherwise, the lower bound of parameter A minus the upper of parameter B divided (median number of parameter B minus the upper bound number of parameter B) minus (median number of parameter A minus the lower bound number of parameter A) should be considered. By looking at this condition that A is greater than B, our result is otherwise 1.208763. This is shown in the second column, row 1 of Table 5. For A greater than C, the median number for parameter A is greater than the median number for parameter C satisfying condition 1. For A greater than D, the median number of parameter A is greater than the median number of parameter D satisfying condition 1. For A greater than E, the median number for parameter A is greater than the median number for parameter E satisfying condition 1. For A greater than F, the median number for A is not greater than the median number for F and hence does not satisfy condition 1. Also, the lower bound number for parameter F is not greater than the upper bound of parameter A and hence does not satisfy condition 0. Otherwise, input the lower bound of parameter F divided by (the median number of parameter F minus the upper bound of parameter F) minus (the median number of parameter A minus the lower bound of parameter A). This gives 1.486011 in column 5 row 5 of Table 5. The computation of the results of other comparisons is made by using this approach and Table 5 will be completed.

The next stage is to calculate the weight vector from the degree of possibility table, which is the minimum of all the values obtained in the range of column 2, row 1 to column 2 row 5. This gives 1. This process is replicated for other groups of comparisons. We obtained 1, 1, 1.1676, 1 and 1 for the respective comparison of B against other parameters, C against other parameters, D against other parameters, E against other parameters and F against other parameters. The next stage into normalize the fuzzy eight vectors. This was accomplished by finding the sum of all the vector weights and then dividing each of them by the sum of the weight vectors. This yielded the following values: 0.1621, 0.1621, 0.1621, 0.1893, 0.1621 and 0.1621. The next step was to obtain Table 6 which shows the multiplication of 0/1 knapsack dynamic programming indices and the fuzzy extent synthetic technique.

Table 6. Combined knapsack, fuzzy extent and fuzzy geometric means methods

Parameters	0/1 KDP	Fextent	01KDP* Fextent	NKS	Fgeometric	01KDP* Fgeometric	NKG
A	0	0.1621	0	0	0.1745	0	0
B	127	0.1621	20.5916	0.0222	0.2062	26.1826	0.0314
C	0	0.1621	0	0	0.1341	0	0
D	0	0.1893	0	0	0.1072	0	0
E	5581	0.1621	904.8940	0.9778	0.1448	808.1331	0.96862
F	0	0.1621	0	0	0.2332	0	0
			925.4856			834.3156	

This is our principal contribution to the literature on exhaust emission optimization in green logistics. The first column contains the input parameters from Benrajesh and Rajan [3]. The second column contains results from the 0/1 KDP scheme earlier implemented in this work. The third column contains normalized fuzzy extent synthetic weight. Column 4 contains the results of the multiplication of 0/1 KDP and the fuzzy extent synthetic weights. Column 5 contains the normalized values from column 4. The final results are 0 for parameter A, 0.0222 for parameter B, 0 for parameters C and D, 0.977751 for parameter E and 0 for parameter F. The interpretation of this is that parameter E has the greatest importance to the achievement of the goal of emission minimization from exhaust pipes. Parameter B has the next important level while parameters A, C, D and F have equal but least importance in the system. Therefore, during budgeting activities, while planning for emission control, parameter E should be given the utmost importance. The outputs of normalization here are the weightage for the EDAS method, which is subsequently applied to this problem. So far, we have obtained the weighting values from the fuzzy extent synthetic technique. However, we will be translating the values to the EDAS method. Thus, the first step is to determine the average solution of each of the input parameters A, B, C, D, E and F from Table 7.

Table 7. Weightage input parameters

	Weights					
	0	0.022249	0	0	0.977751	0
Levels/Parameters	A	B	C	D	E	F
Level 1	52	127	0.77	1.5	5581	1
Level 2	171	1494	16	2.5	43666	1.23E+07
Level 3	287	2861	30.34	3.5	81750	2.46E+07
Total	510	4482	47.11	7.5	130997	36900001
Average	170	1494	15.70333	2.5	43665.67	12300000.3

The first column indicates the different levels of each parameter. The next six columns indicate the input parameters and their values corresponding to the different levels. The first row indicates the combined knapsack and fuzzy extent weightage, which is a multiplication of these two components. Then row 6 indicates the average of each input parameter. After obtaining the average value for these input parameters, we then calculated the positive distance from the average (i.e. PDA) as shown in Table 8. The Equation is used to achieve this goal. Based on the criteria, we need to select beneficial parameters and others, which are not beneficial. Hence beneficial parameters are A, B, C, and E while D and F are non-beneficial parameters. By applying Equation (1), the PDA is obtained forts for column 1, row 2 as 0. This is obtained by getting the maximum number obtainable from parameter A, level 1, which is 52. Then subtract the obtained average of parameter A at all levels divided by the average obtained from parameter A for all levels. The process is applied to the next level value. Thus, column 1 row 3 of the PDA table, containing 5.88E-03 is obtained by the maximum number between zero and the value of level minus the average of parameter A at all levels. This is divided by the average value of parameter A at all levels. Then column 1, row 4 of Table 8 was obtained by choosing a maximum number from 0 and the level 3 value of parameter A. Subtract this from the average value of parameter A at all levels. Then divide this output by the average value of parameter A at all levels. This procedure is replicated for all beneficial parameters A, B, C, and E. Then we consider the non-beneficial parameters of D and F. Parameter D column 4 row 4 showed a value of 0.4, which was obtained by considering the criteria for non-beneficial criteria. The maximum number is obtained from 0 and the average of parameter D at all levels. Then subtract it from the value of parameter D at the level. Then divide the answer by the average of parameter D at all levels. Column 4, row 2 of parameter D shows 0, which was obtained by choosing a number from the maximum of 0 and the average of the parameter at all levels minus the value of parameter D at level 2. Then divide by the average of parameter D at all levels. Next, we approach column 4, row 3, which gives 0 and is obtained by choosing the maximum number from 0 and the average value of parameter D at all levels. Then subtract it from parameter D at level 3. Then divide by the average of parameter D at all levels. This procedure is repeated or non-beneficial parameter E. For the next step, we calculated the weighted positive distance from the average as shown in Table 9.

Table 8. Positive distance from the average

Levels/Parameters	A	B	C	D	E	F
Level 1	0	0	0	0.4	0	0.9999
Level 2	5.88E-03	0	0.0189	0	7.6338E-06	2.71E-08
Level 3	6.88E-01	0.9150	0.9321	0	0.8722	0.00E+00

Table 9. Weight PDA

Levels/ Parameters	A	B	C	D	E	F	SPI
Level 1	0	0	0	0	0	0	0
Level 2	0.00E+00	0	0	0	7.46392E-06	0.00E+00	7.46392E-06
Level 3	0.00E+00	0.020357686	0	0	0.85277514	0.00E+00	0.873132826

The weighted sum of PDA is the same as the weightage multiplied by each set of PDAs as illustrated in Table 8. The weights for input parameters A, B, C, D, E and F are 0, 0.022249, 0, 0, 0.977751 and 0 respectively. Table 9 column 1 row 2 shows the value 0, which was obtained by multiplying the weightage value of input parameter A, which is 0 by the positive distance from the average of parameter A, which is 0. Column 1 row 2 shows the value of 0 which was obtained by multiplying the weightage of parameter A, which is 0 by the positive distance from an average of parameter

1, level 2 value, which is 5.88E-3. Column 1 row 3 shows the value of 0, which was obtained by multiplying the weightage of parameter A, which is 0 by the PDA for level 2 value, which is 6.88E-1. This procedure was replicated for parameters B, C, D, E and F. The next step is to calculate the SPi for the weighted PDA. This is the sum of all the weighted PDAs. This results in the values of 0, 7.46E-6, 0.873133 for the three levels of all input parameters. The next step is to calculate the negative distance from the average for all input parameters as illustrated in Table 10. Row 1 of Table 10 contains all the input parameters A, B, C, D, E and F. The values of negative distance from the average were obtained using the following formula, Equations (4) and (5). Column 1, level 1 value for input parameter A is 0.6941, which was obtained by the maximum number from 0 and the average value of parameter A minus the value of parameter A level 1 divided by the average sum of all parameter A values. Column 1 row 3 shows a value of 0, which was obtained by choosing the maximum from 0 and the average sum of all values of parameter A minus the value id parameter A of level 2 divided by the average sum of parameter A values. Column 1 row 3 shows the value of 0, which was obtained by choosing the maximum number from 0 and the average sum of parameter A values minus the value of parameter A level 3 divided by the average sum of parameter A. This process was repeated for all beneficial input parameters A, B, C and E. Considering the criterion for non-beneficial parameters D and F, we obtain the value of 0 in column 4 row 2 by choosing the maximum number of 0 from the input parameter D of level 1 value minus the average sum of parameter D values divided by the average sum of parameter D values. Column 4 row 3 has a value of 0, which was obtained from the maximum number of 0 and the value of parameter D of level 2 minus the average sum of parameter D values divided by the average sum of parameter D values. Column 4 row 4 has a value of 0.4, which was obtained by choosing the maximum number from 0 and the value of parameter D of level 3 minus the average sum of parameter D values divided by the average sum of parameter D values. This process is repeated for non-beneficial parameter F to complete Table 9, which is the negative distance from the average. The next step is to calculate the weighted NDA as illustrated in Table 11 by multiplying the weightage for each parameter and the value of their respective negative distance from the average.

Table 10. NDA

Levels/ Parameters	A	B	C	D	E	F
Level 1	0.6941	0.9150	0.9510	0	0.8722	0
Level 2	0	0	0	0	0	0.00E+00
Level 3	0	0	0	0.4	0	1.00E+00

Table 11. Weighted NDA

Levels/ Parameters	A	B	C	D	E	F	SNi
Level 1	0	0.0204	0	0	0.8528	0	0.8731
Level 2	0	0	0	0	0	0.00E+00	0
Level 3	0	0	0	0	0	0.00E+00	0

Table 12. Measures of EDAS and ranks

Levels/ Parameters	SPI	SNi	NSPi	NSNi	ASi	Rank
Level 1	0	0.87314	0	0	0	0
Level 2	7.46392E-06	0	1	1	1	1
Level 3	0.873132826	0	1	1	1	1

Table 11 row 1 contains the six input parameters A, B, C, D, E and F. Column 1 row 1 has the value of 0, which was obtained by multiplying the weightage of parameter A with the value of parameter A of level 1. Column 1 row 2 has the value of 0, which was obtained by multiplying the weightage of parameter A with the value of parameter A of level 2. Column 1 row 4 has the value of 0, which was obtained by multiplying the weightage of parameter A with the value of parameter A of level 3. This process is repeated for the remaining parameters B, C, D, E and F. The next step is to calculate the weighted sum of NDAs, which is denoted as SNi. The values of the weighted sum of NDA of levels 1, 2 and 3 are as follows 0.87314, 0, 0. The next step is to calculate the normalized values of the weighted sum of PDAs and NDAs (SPi and SNi). The normalized value of SPi is obtained by the SPi value divided by choosing the maximum number of SPi. As a result, the normalized value of SPi of column 1, row 2 is 0. This was obtained by the value of SPi as level 1 for all input parameters divided by the maximum number from the value of SPi for all input parameters at level 1. Column 1 row 3 has the value 7.46E-6, which was obtained by the value of SPi for all input parameters at level 2 divided by choosing the maximum number of SPi values for all input parameters at level 2. Column 1 row 4 has the value of 0.873133, which was obtained by the value of SPi of all input parameters at level 3 divided by choosing the maximum number of SPi values for all parameters at level 3.

In summary, Table 12 contains SPi, SNi, NSPi, ASi and rank, which means the weighted sum of PDA, a weighted sum of NDA, normalized values of SPi, the normalized value of SNi, the normalized value of the sum of NSPi and NSNi and finally the rank. Column 1 of Table 12 has the values of 0, 7.46E-06, 0.873133 of SPi for all parameters. Column 2 has the values of 0.87314, 0, 0 as the SNi for all parameters. Thus, to obtain the normalized values of SPi in column 3 ow 1, level 1, the value of 0 was obtained by the value of SPi at level 1 divided by the average sum of all values at SPi for all parameters. Column 3 row 3 has the value of 1 which was obtained by the value of SPi at level 2 divided by the average sum of SPi values. Column 3 row 4 has the value of 1, which was obtained by the value of SPi at level 3 divided by the average of the sum of all values of the SPi. Column 4, contains the normalized values of SNi. Column 4 row 1 has the value of 0, which was obtained by the 1 minus the value of SNi at level 1 divided by choosing the maximum number of SNi at level 1. Column 4 row 2 has the value of 1, which was obtained by 1 minus the value of SNi at level 2 divided by choosing the maximum number of SNi at level 2. This process is repeated for column 4 row 4. Next, we calculate the normalized value of combined NSPi and NSNi to obtain NSi in column 5. Column 5 row 2 has the value of 0, which was obtained by finding the average sum of NSPi and NSNi at level 1. Column 5 row 3 has a value of 1, which was obtained by the average sum of NSPi and NSNi at level 2. Column 5 row 3 has a value of 1, which was obtained by the average sum of NSPi and NSNi at level 3. Next, we calculate the rank at each level by giving the highest value rank 1, the next highest value rank 2 and similarly for the rest. In this case, both levels 2 and 3 have the same outcome for normalized SPi and NSNi to have the rank of 1.

Furthermore, the results obtained from the application of fuzzy geometric mean to the exhaust emission optimization problem are discussed. Here, For SP_i levels 1, 2 and 3, the following values were obtained. 0, 7.39 E-6 and 0.8735. The values for SN_i levels 1, 2 and 3 are 0.873531, 0, 0. The percentage difference between the fuzzy geometry means and fuzzy extent is 0.93%, showcasing the fuzzy extent as being higher than the fuzzy geometric mean value. For this result, the values obtained are for level 2 of SP_i. Notice that for level 1 of SP_i, they have the same value of zero. However, for level 3 of SP_i, the percentage difference between fuzzy geometric mean and fuzzy extent synthetic is 0.0448%, indicating fuzzy geometric has a higher value. Now, we move to the values of SN_i. For these values, using the fuzzy geometric mean technique, we obtained the following values of SN_i as 0.8735, 0, and 0 for levels 1,2 and 3, respectively.

The percentage difference of SN_i between the fuzzy geometric mean and fuzzy extent is 0.0448% with the fuzzy geometric mean having higher values of SN_i at level 1. Furthermore, the values for NSP_i, NSN_i, AS_i and ranks for fuzzy geometric mean technique and fuzzy extent synthetic technique are the same across all levels. This means it concluded that the two methods yield almost the same result. In conclusion, level 1 of our input parameters has the least ranking of 0 after using both fuzzy geometric means and fuzzy extent synthetic technique. However, levels 2 and 3 have the same rank of 1 for both methods.

4.1 Peaks and valleys of parameters

In data analysis concerning vehicle exhaust emission, there is the possibility of collecting huge data set in practice the identification of the peaks and valley is therefore essential to have an idea of the range of each parameter for decision-making. For this purpose, the Minitab optimizer of DOE is a useful tool in this regard. Nonetheless, Microsoft Excel offers a useful alternative to the optimizer provided by Minitab software 16. Therefore for simplicity, we will deploy Microsoft Excel spreadsheet version 2016. This has the advantage of obtaining the maximum and minimum values which are equivalent to the peak and valley of each parameter. Implementation of the method proposed in this work will be made easier by adopting the Microsoft Excel 2016 spreadsheet used by the logistics manager. The method uses the function, Max and Min. The operation is performed by typing "=max". Then select the arrays of values. The result that emerged after such an operation on our data for parameters A, B, C, D, E and F are as follows; the respective maximum and minimum values are {287,52} for A, {2861,127} for B, {30.34,0.77} for C, {3.5,1.5} for D, {815750,5581} for E and {24600000,1} for F.

4.2 Advantages of the fuzzy-0/1 knapsack dynamic programming-equal distance from the average solution (F-0/1 KDP- EDAS) method

The new method, the F-0/1 KDP-EDAS method offers unique advantages regarding uncertainty, optimization and selection each of which may be derived from the individual components of the method. Interestingly, the first component of the F-0/1 KDP-EDAS method is the fuzzy extent analysis component that was brought into the combination method to tackle uncertainty. The fuzzy extent analysis has its root within the fuzzy analytic hierarchy process framework and is well known among researchers for its robustness in tackling uncertainty, improving (reducing) it to attain the goal of the system, for instance, the reduction of vehicle exhaust emission from the packing vehicles in the packaging industry. The mechanism of operation of fuzzy extent analysis is the application of the idea of extent analysis that showcases the degree that the parameters in the exhaust emission process achieve the minimization of the emission goal. Interestingly, the satisfied extent, which is the same as the "achieved extent" emphasizes that the goal has been attained. Now, the extent analysis deploys features of the idea of the extent to combine with the degree of possibility in the computation of the weights arising from the fuzzy comparison matrices.

Moreover, the 0/1 knapsack dynamic programming has the key advantage that it is extremely straightforward to comprehend and consistent. Besides, the optimal solution offered by the 0/1 knapsack method is such that it cannot mar the outcome established with this approach. Furthermore, the EDAS method brings advantages to the F-0/1 KDP-EDAS method from the following perspectives. The EDAS method eradicates the risk of biasedness by decision-makers through the computations of negative and positive distances from the average solution. Next, the use of positive and negative distances from its average aids normalization. Also, the EDAS method evades the extreme distance of an option from the worst or best solution.

Owing to these benefits, the F-0/1 KDP-EDAS is investigated in the article to cover the optimization idea and the multicriteria analysis from the perspective of uncertainty reduction. However, there is an absence of any study on EDAS with a combination of fuzzy extent analysis/fuzzy geometric means and the 0/1 knapsack dynamic programming. In this case, a concurrent optimization and selection of exhaust emission parameters in the packing industry have not been previously reported. This is a research gap addressed in the present article.

4.3 Research implications

The findings of this research reveal multiple managerial implications. First, the study results reveal some parameters that are crucial in explaining the exhaust emission process for the packing industry. While six parameters were chosen for analysis, through the application of the 0/1 knapsack dynamic programme quantity consumed was streamlined as the more influential parameter for the determination and control of emissions from vehicles in packing industries. Thus, stricter control of the quantity consumed may be promoted by the management of the organization. Enlightenment programmes for new drivers of vehicles used for goods delivery in the packing industry should be initiated and intensified. This brings consciousness when drivers know that as the packing industry that they represent is penalized, they are also affected by the loss of some benefits attached to pollution-free motoring. For instance, some drivers may ignore the devastated stage of a delivery vehicle, which gives out emissions unusually due to the long-due service, up till now not attended to by the driver. To demonstrate openness, companies can adopt a booking scheme where the state of the engine is declared before the approval to embark on the journey, given by the maintenance or fleet engineer in the company. This could trigger a meeting to discuss any concern on the emission-motivated problem by the engines of the vehicles. Based on this booking system, the belief that drivers adhere to operating principles is strengthened if the measures indicated in the booking are communicated among drivers and also discussed with all drivers in meetings, furthermore, although the parameters included in this research have been previously analysed in a study by Benrajesh and Rajan [3]. However, the parameters have not been analysed from the perspective of uncertainty in the exhaust emission analysis in packing industries. Based on the findings of the present research, several key implications may be drawn for the packing industries in a managerial context. Notwithstanding, uncertainty analysis has a unique nature, which managers of packing industries should know.

5. Conclusions

In this paper, a new method, the F-0/1 KDP-EDAS method, applied to the reduction of exhaust emissions from the packing industry due to vehicle usage, was presented. The information obtained from a literature source by Benrajesh and Rajan [3] was first extracted and transformed from the crisp numeric values to the linguistic terms in fuzzy from the perspectives of the fuzzy synthetic extent and fuzzy geometric applications. Then the 0/1 knapsack dynamic programming was applied to the problem to obtain the optimal values, which were then united with the fuzzy weights and afterwards used as the criteria weight for the EDAS method before the final computation. Based on the study, the following conclusions were drawn from the findings: with the six parameters evaluated, notably parameters A, B, C, D, E and F, the most important parameters are parameters B and E from the knapsack analysis: next, it is concluded that the integrated method is feasible in its application to an Indian environment.

The limitation identified in this study provides several opportunities to further extend the research. However, due to the use of field data already collected by Benrajesh and Rajan [3], it is not possible to identify more than three parameters in the group of parameters studied that are relevant to the value and weight criteria determination. This creates repetitions of data when restricting the data to work on to normalized data. As such it becomes difficult to differentiate the importance of one parameter against the other for the choice of optimal values of parameters for the emission control problem. It would be interesting if future studies can extend the parameters associated with the value and weight criteria to several rows and three criteria could be considered to permit more representative normalized values. This will show adequately the interactions among the parameters of interest and the optimal values.

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