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Vehicle Exhausts Emission Pattern Decisions for Logistic Services and Packing Industries with Orthogonal Array-Based Rough Set Theory

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ABSTRACT

Precise monitoring of vehicle emissions in green logistics, focusing on the contributions of vehicles from packing industries, is crucial for many issues. It helps to understand the total emissions and gain insights into the mechanism of vehicle-associated environmental concerns. Notwithstanding, a key issue when monitoring vehicle emissions is the effective discrimination problem for different patterns generated from the parameters. Data from the packing industry are available from distribution networks but its pattern cannot be discriminated. Given this background, this article presents a new method of the orthogonal array-based rough set to discern patterns of the parametric behaviors to monitor emissions from vehicle exhausts in the packing industry. The proposed method is based on an Indian logistics network and delivery system data, which was obtained from previous work in the literature. By setting controls on the parameters of the packing industry which includes revenue obtained, packing units sold, growth rate, carbon-dioxide equivalent, materials utilized, and quantity consumed, the method was able to discern the patterns of the parametric behavior. The orthogonal arrays, which are developed, form factors (parameters) and levels to ascertain a balanced and uniform analysis of the various groups of options. Indiscernibility and approximation concepts of fuzzy sets are then applied to arrive at the outcome. Unlike previous studies, this study eliminates the need for tracking data, assumptions, and external information to establish the set membership. However, it utilizes the available information within the data. The rough set analysis indicates that there are no discernable patterns or rules that distinguish between "Yes" and "No" decisions. The method of rough set illustrated in this work shows the feasibility of the approach in the Indian packing industry. The method is useful for the logistics manager and government agencies responsible for the control of vehicle-generated greenhouse emissions.

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1. INTRODUCTION

Packing industry vehicles are the major sources of carbon emissions. Moreover, climate abatement policies and actions have been developed to monitor these carbon emissions. However, the precise prevention and monitoring of vehicle emissions has been compelling for researchers. Consequently, vehicular emission patterns remain a viable option for attaining this objective. Furthermore, vehicular emission patterns carry a wealth of information, offering opportunities to communicate monitoring ideas and providing a consistent method for solving emission problems. However, a key issue when monitoring vehicle emissions is the effective discrimination problem for different patterns generated from the parameters. Nevertheless, nowadays, green logistics in logistics networks and delivery systems have been discussed on a large quantitative basis and the focus is usually on sustainability (Wu, 2022; Ju et al., 2023; Maji et al., 2023; Mugoni et al., 2023). For example, Islam et al. (2021) considered the carbon dioxide emission from vehicles and introduced a metaheuristic that combines particle swarm optimization and neighborhood search to model the problem. Also, Ugarte et al. (2016) considered the influence of the current best practices conducted in lean logistics on the environment. A simulated method was adopted for the empirical testing of a manufacturing-retail supply chain (Ugarte et al., 2016).

From the perspective of the Indian logistics network and delivery system, the environmental impact of vehicle exhaust emission on the Indian environment can be minimized in different forms (Kumar et al., 2018; Rajput et al., 2019; Singh et al., 2020). For example, approximating general functions such as Fourier series, polynomials, finite elements, and rough sets are well-known tools of interventions in the minimization of certain phenomena in the science literature. However, such models are downplayed in environmental impact assessment within the Indian logistics network and delivery system. This paper aims to minimize greenhouse gas emissions in the packing industries and delivery systems. In the Indian packing industries, the classified types are of two groups. One group consists of the ancillary, primary, secondary, and tertiary packaging. The other group is based on the material type used for the packaging which includes glass, plastic, metals, paperboard, and paper. Interestingly, the size, share analysis, and growth pattern of the packaging industry in India in the 2023-2028-year range, according to Mordor Intelligence (2023) was declared as impressive. Particularly, the Indian packing market size is estimated at USD71.90 billion in 2023 and it is expected to grow to USD 130.14 billion in 2028.

From these statistics, the Indian community has an enormous interest in packing products where a significant part of these products are consumed locally before considering the export market. Therefore, the emissions from the vehicle exhausts used in the Indian logistics network and delivery system need to be minimized. This is the greenhouse emission that will be minimized by the model produced in the present study. Among the aforementioned approximating general functions, the rough set is the most appropriate one to tackle the current environmental impact problem in India as it requires no preparatory or supplementary information about the logistics network and delivery system data provided in Benrajesh and Johnrajan (2019). Besides, information on the statistical probability distribution and other items is not needed while deploying the fuzzy set theory. Therefore, in this work, the rough set method is assumed for the analysis of the vehicle exhaust emission process in the framework of the data collected by Benrajesh and Johnrajan (2019).

In the rough set method of this work, it is conceptualized that revenue is earned by the packing industry for each year of operation. However, the analysis will be based on only one year at a time. The packing units sold are monitored and recorded and a compound annual growth rate is also assumed, which corresponds to the reference year for the revenue obtained. Besides, concern is shown for the material used in the packaging system. Furthermore, the quantity of material consumed in Kilo is noted and this is also linked to the carbon dioxide equivalent for the packing materials used in the logistics and delivery system. The above information could be verified by Benrajesh and Johnrajan (2019) whose data is used for the present analysis.

Interestingly, logistics networks and delivery systems as a subject have been discussed in the literature and the Indian scenario has remained at the centre of certain discussions. However, to the best of our knowledge, the issue of inductions of approximations of vehicle exhaust emission concept has been rarely discussed in articles on logistic networks and delivery systems. Particularly, the topic of knowledge discovery in the database of the Indian packing industry marked regarding logistic network and delivery system to discover patterns hidden in the logistics and delivery data, using the rough set has not been discussed in previous studies. Consequently, the principal novelty of this article is to fill this gap in the perspective described above. In addition, the proposed method does not require elaborate statistical data on probability and related issues, making it easy to implement where there is a paucity of data. To sum up, this article presents a rough set method on the vehicular exhaust emission process to know and control how much pollution from vehicles is produced by the logistic network and delivery vehicles in India. This will help the monitoring and regulatory body to have standards for the control of pollution in the Indian environment.

Pollution adversely influences the health condition of humans and the surrounding air quality in the environment. Considering the rough set method for the vehicle exhaust emission analysis, government agencies such as the Ministry of Road Transportation and Highways and associated organizations and associations such as the standing committee on the implementation of emission legislation in India can update their standards and include the proposed method as a regulatory framework in the presented method, the orthogonal array is offered to make the implementation of the method easy. With this method, limited data is needed such as the specification of the parameters (factors) affecting the emissions and the adoption of a level framework. The orthogonal array, which is developed from the factors and levels using statistical software such as Minitab Software 2020 (version 16), ascertains that a balanced and uniform analysis of the various groups of options is considered. For a large parametric set, an orthogonal array permits data testing for interactions using the least number of cases. This method leads to indiscernibility concepts, which analyze parameters such as the revenue obtained, packing units sold, compound annual growth, materials used for packaging, quantity consumed, and carbon dioxide equivalent. It takes different sets of a particular parameter from the similarity in the translated values of their levels. It then compares these sets (i.e. elementary set) and forms a judgment about the formation of an equivalence set from these elementary sets. It determines if they have the same properties or not. Thus, the orthogonal framework based on the orthogonal theory that forms the foundation of optimization for the Taguchi method has been applied in connection with a rough set. It solves the vehicle exhaust emission approximation (minimization) problem.

Compared to Li et al. (2023), Bai et al. (2023), and Kang and Tan (2023), this paper proposes a method of fuel consumption reduction leading to reduced carbon emissions in a green logistics network and delivery system. The analysis presented in our work results in the elimination of the requirements for equilibrium strategies required by Li et al. (2023). It avoids the need for information on government subsidies to banks (see Bai et al., 2023) and concerns the free-rider problem (see Kang and Tan, 2023). In this article, a new method to monitor the emissions from vehicle exhausts of distribution vehicles in the packing industry is presented. The method is based on the orthogonal array coupled with the rough set to discern patterns of the parametric behavior to monitor emissions from vehicle exhausts in the packing industry. The proposed method is based on an Indian logistics network and delivery system data, which was obtained from previous work in the literature (i.e. Benrajesh and Johnrajan (2019)).

In the work, we used the rough set method and not another approximation method since differently from other methods such as finite element, decision-makers reevaluate the thresholds of levels without falling back on complex statistical analysis. Besides, the rough set has the following advantages. It demonstrates the capability to operate in a strong obtained manner using the original data set. Thus, the contribution of this work would be as follows:

1. Establishing a rough set method based on the knowledge discovery of key vocabulary emissions data from exhausts in the packing industry in India. This will encourage government agencies and committees such as the Standing Committee on the Implementation of Emission Legislation in India to contribute to improving the emission standards set for the Indian environment.
2. Introducing the functional approximation concept of the rough set for emission reduction from vehicles. This concept is suitable for other countries, particularly developing countries.
3. The rough set method introduced in this work has extremely limited requirements for data. It, therefore, helps emission agencies to function properly even in the absence of abundant data. Thus the rough set is useful even when the company hoards data to the regulatory agency.

The next section presents the literature review. The method section follows this. The results and discussion section follows this. Finally, the concluding remarks are given:

2. LITERATURE REVIEW

Besides the studies discussed in the introduction, several other studies have proposed new methods and have successfully implemented them. The following is a brief survey of such studies: Yang and Zhou (2020) use decision tree analysis to quantify influencing factors of importance to CO_2 emission from various trips. It has been discovered that varying factors influence CO_2 emission. Rahman et al. (2023) proposed the decision tree variants to estimate the greenhouse gas emissions produced in Saudi Arabia and found out superior (the highest) value of the coefficient of determination from the bagged decision tree variant based on the data set. The method was then judged as reliable. Stokić et al. (2023) predicted with the bilinear interpolation method to determine the emission of various vehicle types and validated the model. Deveci et al. (2022) applied the DIBR (Defining Interrelationships Between Ranked) criteria and the COCOSO (COmbined COmpromise Solution) method in a zero-emission logistic drive. Zhang et al. (2018) proposed an optimized bi-level formulated model while introducing a Frank-Wolfe hybrid algorithm in incorporating logistics infrastructure assets and subsidies for green transportation aimed at obtaining particular CO emission goals. Their finding is that it is more effective to use a combined choice of logistics infrastructure assets and green subsidies instead of deploying them only for carbon emission reduction.

Anttila et al. (2022) evaluated CO_2 emission by deploying an artificial intelligence big data approach with consideration to transportation factors like truck models and weather variables in Finland. It was discovered that driving speed was the most influential variable in emission generation. Melo and Baptista (2017) evaluated the impact of electric cargo bikes to minimize the negative influence of CO_2 emission using the advanced interactive microscopic simulator for urban and non-urban networks (AIMSUN 8.1.2 version) in Portugal. Urban logistics WTW CO_2 emission was reduced by up to 73% representing 746 kg of CO_2 evaded emissions. Wang et al. (2021) applied emission rate models to assess the diverse influence of loading states for DSTTTS (diesel semi-trailer towing trucks' greenhouse emissions). Results from STP distribution revealed that the emission rate of CO_2, CO, and total hydrocarbon for DSTTTS considering complete loaded situations exceeds those of unloaded situations. Jaiswal et al. (2021) solved the problem of greening the supply chain concept through the development of a pollution optimization model aimed at minimizing emissions and reduce the cost of transportation during the logistics cost of transportation during the logistics process.

Moreover, random forest algorithms have been used to extract emission patterns. Khajavi and Rastgoo (2023) introduced a hybrid of random forest, response surface method, and support vector regression as a computational intelligence framework to predict CO_2 emission in China's road transport. The significant result is that the best accuracy of the R^2 value of 0.9641 was obtained using a combination of support vector regression and Harris Hawk optimizer. Wang et al. (2018) proposed a NO_x emission method for a power plant using a joint method of enhanced random forest and a feature re-oriented enhanced binary flower pollination scheme. The significant result is that combining the random forest algorithm with the flower pollination scheme yielded enhanced robustness and higher accuracy in prediction than the basic random forest scheme. Leo et al. (2024) predicted the emissions from a compression ignition-direct injection engine using the random forest algorithm. The emissions attributes of waste cooking oil biodiesel together with premixed aluminum oxide, ferric chloride, and gasoline were investigated. The significant result of the use of the waste cooking oil biodiesel mixture exhibited a great reduction in emissions. It was reported that smote emission, hydrocarbon, and carbon dioxide were reduced by 22.69%, 54.17%, and 50% respectively.

Ma et al. (2023) deployed a random forest algorithm-based method to predict the NO_x emission in a coal-fired power plant. The enhancements to the random forest model are the introduction of the convolutional neural network, Chaos strategy, and iterative local search. The significant result is that the proposed model demonstrated an accurate prediction of the NOx emission from the power plant. Zhang et al. (2023) employed the random forest algorithm to predict and control CO_2 emissions in Chinese cities. The most important result is that random forests exhibited a more accurate prediction of CO_2 emissions than other predictive methods. De. Lima Nogueira et al. (2023) used a random forest model to predict diesel engine emissions. The random forest algorithm was enhanced with the Parzen estimator and feature engineering method. The most significant result is that the random forests method revealed a correct prediction of the emission signals from the diesel engine. Wang et al. (2023) used a random forest algorithm to evaluate the NO_x emission for a power plant. The significant result is that the random forest model exhibited superiority over five other methods using data sets from two power plants. Le Cornec et al. (2020) applied a combination of models, including dynamic time warping, cluster analysis, neural network multi-layer perception, non-linear regression, and look-up table methods to a dataset in a real-world driving condition for emission monitoring. The models were effective in developing emission inventories.

In the above literature, pitfalls to violating environmental regulations and legislations have been suggested by the proposition of measurement methods, which play important roles in guiding compliance with government regulations on the environment. Government standards on regulations have been used frequently by logistic managers in industries. Moreover, their attention has been focused largely on the maintenance of vehicles that are fit for roads. These vehicles have engines that minimally emit harmful gases into the atmosphere. In this case, oxides of nitrogen, carbon monoxide, and sulfur oxides have been tested for their limits in emissions during vehicular repairs. Vehicles that are not complying are dumped and sold out. However, it is known that this method is subjective and could lead to incorrect decisions on knowing the threshold of emissions on roads when their vehicles ply roads in the logistic network and delivery services. Therefore, more reliable methods such as game theory (Kang and Tan, 2023), clustered method (Islam et al., 2023), decision methods (Bai et al., 2023), and empirical analysis (Ugarte et al., 2016) have been employed previously. Successful data inputs and the form of analysis may be complex thereby distorting the presentation of the ideas of such methods to the productions. besides, the cost of gathering such data may be prohibitively high. Then, it is correct to subscribe the lingering environmental impact reduction problem to the difficulty of diffusing the learned knowledge to the practitioners in the company. Therefore, an alternative route to reducing this burden to practitioners and guaranteeing the diffusion of the method to the user is the development of a simple method. This method eliminates the requirement of huge data sets for functioning. Thus, the contribution of a rough set method to vehicular exhaust emission analysis, proposed in the present study satisfies this literature gap.

To the best of the authors' knowledge, no studies have employed orthogonal array-oriented rough set theory to achieve a deep understanding of the different patterns that could be generated from the parameters of vehicle emissions in a packing industry through an interface with the experimental trials obtained from real-life field data. The effort is to ultimately improve planning and decision-making on emission control at various distribution routes. However, as reported in the literature review, only a limited number of investigations have used the random forest algorithm to predict emissions from the system (Khajavi and Rastgoo, 2023; Wang et al., 2018; Leo et al., 2024). Few studies have used other machine learning techniques (Le Cornec et al., 2020) others have used decision tree variants for emission estimations (Rahman al., 2023; Yang and Zhou, 2020). Still others have used the multicriteria method (Deveci et al., 2022). Big data approach (Anttial et al.,2022). In all these methods, the data available to generate the models excluded those of the packing industry in logistic services. Also, none of the studies has localized the methods to the Indian environment. Consequently, in this study, real-world data from the packing industry, which was earlier reported in the literature was used as the dataset for the present study. It comprises of six parameters carefully chosen by Benrajesh and Johnrajan (2019) to represent the operations of the Indian packing industry. Three levels were originally reported by Benrajesh and Johnrajan (2019). However, a unique integration of the levels into two was made for a robust and precise pattern development for the emission data of the packing industry.

3. METHOD

The rough set method was innovated by Painlak (Pawlak, 1982, 1992), first in 1982 and then substantially improved upon in 1992. The discovery intends to help in dealing with imperfect knowledge. Imperfect knowledge refers to unforeseeable structural changes in the emission data, in the present case. This structural change may be due to the data collection personnel. Such errors may be severe and could distort information leading us to make incorrect conclusions and on the data for emulsion control decisions. Interesting information on rough sets can be seen in Skowron and Dutta (2018). Fuzzy sets are probed for their indiscernibility and approximation contained in the rough set. Approximations in two modes are then created. The first mode of approximation is meant for the lower limit while the second mode of approximation is meant for the lower limit while the second mode of approximation is for the upper limits. The Polish scientist (Zdzislaw Pawlak) who invented the rough set proposed that the rough set is an approximation method, which works on the crisp numerical values, as a set of members. Pairs of numbers in the set are considered and segregated into lower and upper approximations. These numbers are called the crisp sets. A rough set, as deployed in the present study, is a combined orthogonal array-based study with the approximation tendency in a rough set used to compare conditions and decision attributes of an object or process. In this particular case, the attributes of interest are the parameters of the vehicle exhaust system which are A, B, C, D, E, and F. Basically, if we let I = (A_u), where A_u is the information concerning parameter A, given as renature obtained in logistics services, Au = (A_A, A_B) where A_A is a non-empty set and A_B is also a non-empty set. But Au is the universal set of the data that is generated on revenue obtained. Each of A_A and A_B is a finite set of attributes of the vehicle emulsion system. It is known that $A_u \rightarrow A_A \rightarrow X_A$ for every b A_B is the set of attributes that B may assume.

Furthermore, in discussing rough sets, six principal pillars are of concern, namely, indiscernibility, rough membership, information systems, set approximation, decision systems, and dependency on attributes. However, to understand the totality of the rough set idea, some of these concepts are explained. The rough membership explains the levels of association of the conditional and decision characteristics of an information system. The center of attention is placed on the location of the subjects in the context of the universe of discourse. It may be explained as a form of cardinality or probabilistic. Moreover, to tackle set approximation, two main categories may come to mind, two main categories may come to mind, notably the lower and upper approximations. Often, the lower approximation is defined as RX where the union of Xs, comprises subjects—the other definition is such that the union of subjects containing X is specified. Thus, from the viewpoint of the rough set, a set X may be defined as negative to definable sets in A which utilizes RX and R-X to elaborate on the indiscernibility of three aspects. The term indiscernibility refers to the attribute slowing inability to perceive the element in distribution from another element. Next is the dependency of attributes, which reflects the ability of particular attributes of a system to control the characteristics of other attributes. This brings the idea of evaluating the influence of an attribute regarded as the source on the target attribute. Notwithstanding, information systems integrate the idea of hardware, and software to extract important information from the logistic network. Furthermore, decision systems are groups of activities involving sequential determination and judgment of logistic services data.

The following steps explain how to determine the rough set characteristics of the vehicle exhaust emission process by focusing on its parameters.

Step 1: Develop an information system or table: To examine the parameters and their attributes that reflect the qualities that hold the key to understanding the data set.

Step 2: Indiscernibility: To unravel the uncertainty, objects are grouped with others that share similar attributes into elementary and Equivalence Classes. Objects within the same class were like companions on a shared journey, and their unity reveals hidden truths about the data. That is, for each combination of condition attributes (A, B, and C), it identifies which data points have the same values. These data points are indiscernible concerning the selected condition attributes.

Step 2.1: Consider the alternatives or attributes to determine the relationship

Step 2.2: Obtain the elementary set

Step 2.3: Find the equivalence classes

Step 3: Set approximation

Step 3.1: Find the lower approximation (definite answer/positive region)

Step 3.2: Find the upper approximation (possible answer)

Step 3.3: Find the boundary region

Step 3.4: Find the negative/ outside region

More importantly, the specific problem is that logistics managers in the parking industry desire to combat emissions from their fleet of vehicles used in delivery services. However, they do not have a basis regarding what arrangement of the experimental trials in the taxonomical group with each parameter of the emission concerning each parameter of the emission process. The logistic managers are also unaware of to what extent each parameter of the logistics network contributes to the emissions given out in the environment Published studies have focused greatly on the signal–to–noise ratios obtained from the Taguchi methodical computations. A huge emphasis on the optimal thresholds of each process parameter is made at the expense of a deep insight into the approximate of the imprecision inconsistent and uncertain knowledge in the emission data collected from the field for analysis. Thus, continuing to innovate with optimal results of parameters concerning emissions in the parking industry in the absence of understanding such pattern of emissions within the parking industry results in the parking industry expending substantial effort time, and funds on emission control planning without fully harnessing the power of uncertainty reduction and using preferred criteria to monitor patterns to the advantage of the parking industry. Bridging the gap between parametric data classification to obtain structural association of parameters regarding emission in the context of imprecise data as a viable and valuable avenue of evaluating the performance of parking industries concerning emission control is an essential step towards the effective control of emissions from vehicles in parking industries. Logistic managers may deploy this knowledge gained from the present work to inform the development and effective utilization of emission control methods in their organizations.

4. RESULTS AND DISCUSSIONS

The basic idea of rough set application to the exhaust emission process is to establish a structural association among the parameters of the exhaust emission process. To achieve this goal, any process that may be simplified as consisting of factors and levels may be used. The use of factors and levels is consistent with past findings as in Benrajesh and Johrajan (2019). A concern is how to determine the level of parameters to use in evaluations. This depends on what one knows about the parameters. The researcher needs to determine the economic number of counts of data to obtain the parameter and then collect it. For the convenience of using the orthogonal array to choose a configuration for the signal-to-noise ratios, three levels are suggested as the maximum. Choosing levels above this threshold implies the challenge of finding a suitable orthogonal array using software such as the Minitab 18. Three levels are obtained from the data when all the data collected on a parameter are distinguished into three aspects such that the average of each distinction is made to represent a level. Moreover, the researcher could reduce the number of levels to two if there is a paucity of data. It should be noted that data segregated into two levels will still work well for signal-to-noise computations despite the paucity of data that exists in the situation.

For the method's application in a real-life scenario, data from Benrajesh and Johnrajan (2019) was used, represented by parameters A, B, C, D, E, and F. The representation of these parameters is as follows: Parameter A, which is the achieved revenue of the parking industry is measured for one year and was expressed in million dollars in the original data. However, a base period of 2015 is assumed. This is also known as the sales. In real life, the sales made by the company should depend on other issues such as budgets for sales operations, marketing drive and skill of the employees, the ability of the company to overcome and handle completion, and other factors. There could also be the quality of delivery service of the parking industry. However, it is assumed that all these issues have an extremely little influence on the revenue declared by the parking industry at the end of the 2015 year of reference. It could also be assumed that the stated issues are managed efficiently so as not to affect the amount of revenue generated. The parameter B is the packing units sold, which is expressed in billions. Next is parameter C, which is often described as the compound animal growth rate. It is measured concerning the base year of 2015 as declared in the present case study data examined in this work parameter D represents the materials used for packing. Parameter E shows the quantity of materials consumed, expressed in kilotons. Parameter F is the CO2e of the packing, which is the equivalence of the carbon dioxide, which is a product of the greenhouse. In our case, a six-parameter three-level platform is created. The parameters are A, B, C, D, E, and F while the levels are 1,2 and 3 (Table 1).

Table 1. Parameters Vs Levels

Parameters	Level 1	Level 2	Level 3
A	52	171	287
B	127	1494	2861
C	0.77	16	30.34
D	1.5	2.5	3.5
E	5581	43666	81750
F	1	12300000	24600000

(Benrajesh and Johnrajan, 2019)

Notice that it would have been easy if many of the entries of each parameter had similarities with each other. For instance if for parameter A the values 52 had been repeated in level 2 also. And we have similar repetitions across the whole parameters. This may not be so because designing the parametric levels captures different values of the parameters. Hence, for parameter A we could not find any of levels 1, 2, and 3 being equal. It then means that for us to apply the rough set technique, orthogonal arrays must be introduced. However, the next stage in the evaluation is to simplify several levels to the least possible. In this case, the three levels are reduced to two (Table 2).

Table 2. Average of levels

	Average level 1	**Average level 2**
	(L1+L2)/2	(L1+L3)/2
A	111.5	169.5
B	810.5	1494
C	8.385	15.555
D	2	2.5
E	24623.5	43665.5
F	6150001	12300001

In Table 2, the results of merging levels 1 and 2 and finding the average are shown in the second column. The third column is the average of levels 1 and 3. Therefore for parameters A when 52 and 171 of levels 1 and 2 are calculated for an average, a value of 111.5 is obtained. This is in cell A1. By similar computation of average of 52 and 287 of parameter A for levels 1 and 3 is obtained. Then a value of 169.5 is obtained. We are then left with twelve values in Table 2 as opposed to eighteen values for all parameters in Table 1. The next step is to generate an orthogonal array consisting of 6 factors and 2 levels. In this case, an L8 orthogonal array emerges (Table 3) notice that the orthogonal array may be extracted from the Minitab 2020 (version 16).

The layout of the table which consist of integers 1 and 2 only represents the various levels of the parameters. A new table which is a translation of Table 3 is produced as table 4. In Table 4 only the rows containing eight experimental trials and the columns which are the parameters namely A, B, C, D, E, and F are considered.

Now it is interesting to obtain the values at the intersection of row 1 and column A. This value is the equivalence of integer 1. But integer 1 has a translated value of 111.5. Accordingly, all other integers that represent levels for various parameters are translated and shown in Table 4.

Table 3. L8 orthogonal array

Experimental trial	Parameters					
	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	1	1	2	2	2
3	1	2	2	1	1	2
4	1	2	2	2	2	1
5	2	1	2	1	2	1
6	2	1	2	2	1	2
7	2	2	1	1	2	2
8	2	2	1	2	1	1

One of the columns involves decision-making where a YES or NO decision is to be made. However, during the experimental trial, we observed a common pattern of behavior in the data. Considering experimental trial 1. Column B has a value of 810.5 which is greater than the value of 111.5 in column A. Furthermore, column C has a value of 8.385 which is less than the values in column B and column A. Moreover, column D has a value of 2 which is less than the values of columns A, B, and C. Also column E has a value of 24623.5 which is greater than the values of columns A, B, C, and D. Then column F has a value of 6150001 which is greater than the values of all other columns A, B, C, D and E. This same pattern is common for all the experimental trials. Therefore, it is difficult to make a YES or No decision concerning the acceptance or rejection of an experimental trial. Notice that a YES accepts an experimental trial while a NO rejects the experimental trial. To overcome this barrier, decisions are generated randomly over the 8 experimental trials. In this decision-making, a table of random numbers was used. Extraction from this table shows that the following ordered random numbers are applicable in our situation;61424, 90222, 50349, 85676, 02429, 90519, 26631, and 89990. To apply these random numbers, we consider experimental trial 1 first. The first random number is 61424 and the first digit of this random number is 6. The digit 6 falls within the experimental count of 1 to 8. Therefore, the first experimental trial is given a "YES" decision moving on to experimental trial 2, the second random number is 90222. The first digit of this random number is 9 which falls outside experimental trials 1 to 8. Therefore, experimental trial 2 is given a "NO" decision. Besides, the third random number is 50349. The first digit which is 5 falls within experimental trials 1 to 8. Therefore, experimental trial 3 is given a "YES" decision. We similarly considered the fourth, fifth, sixth, seventh, and eighth random numbers. These are 85676, 02429, 90519, 26631 and 89990. The results of the decisions are YES, NO, NO, YES, and YES respectively.

The next step is to evaluate the indiscernibility association of the parameters. By indiscernibility, we set to find the relationship between two or more parameters in the universe. To proceed, we need to understand the two terms that are important to us in achieving the indiscernibility of the information we are providing. The elementary set is the first while the equivalence set is the second term. The elementary set is the main foundation concerning our knowledge about the main reality. This term is often used for all indiscernible objects indicating similar objects. By looking at Table 4 we will notice that the value 111.5 is repeated in cells A_1, A_2, A_3, and A_4. This makes the first elementary set. Notice that parameter A will be referred to as IND A which is the short form of indiscernibility of parameter A. Notice also in Table 4 the cells at the positions of A_1, A_2, A_3, and A_4 will be labeled as X_1, X_2, X_3 and X_4. In other words, X_1, X_2, X_3, and X_4 are the first components of the elementary set for parameter A. Also note that for parameter A, the cells named A_5, A_6, A_7, and A_8 contain the same value of 169.5. for these cells, since the numbers are the same they are called the second component of the elementary set of parameter A. Notice also that A_5, A_6, A_7, and A_8 will be replaced with X_5, X_6, X_7, and X_8. Still referring to Table 5 we may draw up information on the two elementary sets for parameter A as Equations (1) and (2). Here, we are starting with the elementary set A. This is a collection of objects S_1 and S_2 (Equations (1) and (2), respectively).

Elementary set A (Table 5)

$$S_1 = \{X_1, X_2, X_3, X_4\} \tag{1}$$

$$S_2 = \{X_5, X_6, X_7, X_8\} \tag{2}$$

Here, the merging of the two sets is called the union of S_1 and S_2, which is denoted as a cup placed between S_1 and S_2 to give equation 3. It will be noted that in Table 4, the pattern of distribution of elements is not the same. Therefore, we will do this analysis on the individual parameters. Now we move to parameter B and read values from Table 4 for parameter B. The principle behind the segregation of numbers into elementary sets will still be used. It will be noticed that cells B_1 and B_2 have the same number. Also, down along parameter B and in cells B_5 and B_6, 810.5 is repeated. Therefore, it is reasonable to group the elements having this number 810.5 together. Notice that if we are to look at the positions where 810.5 is written, each of the positions can be designated as X_1, X_2, X_5, and X_6. Therefore, we will write this as the first elementary set. Thus, Equation (4) is valid.

Equivalence set

$$S_1US_2 = \{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\} \tag{3}$$

Elementary set B

$$S_3 = \{X_1, X_2, X_5, X_6\} \tag{4}$$

$$S_4 = \{X_3, X_4, X_7, X_8\} \tag{5}$$

By reasoning along the same dimension, the second elementary set consists of cells at positions B_3, B_4, B_7, and B_8. Therefore, Equation (5) is valid. In this respect, the union of S_3 and S_4 gives an equivalence set of Equation (6). For parameters C to F the same principle was applied and the following Equations (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17) and (18).

Equivalence set B

$$S_3US_4 = \{\{X_1, X_2, X_5, X_6\}, \{X_3, X_4, X_7, X_8\}\} \tag{6}$$

Elementary set C

$$S_5 = \{X_1, X_2, X_7, X_8\} \tag{7}$$

$$S_6 = \{X_3, X_4, X_5, X_6\} \tag{8}$$

Equivalence set C

$$S_5US_6 = \{\{X_1, X_2, X_7, X_8\}, \{X_3, X_4, X_5, X_6\}\} \tag{9}$$

Table 4. Rough set information table

Experimental trial	Parameters						Decisions
	A	B	C	D	E	F	
1	111.5	810.5	8.385	2.0	24623.5	6150001	Yes
2	111.5	810.5	8.385	2.5	43665.5	12300001	No
3	111.5	1494.0	15.555	2.0	24623.5	12300001	Yes
4	111.5	1494.0	15.555	2.5	43665.5	6150001	Yes
5	169.5	810.5	15.555	2.0	43665.5	6150001	No
6	169.5	810.5	15.555	2.5	24623.5	12300001	No
7	169.5	1494.0	8.385	2.0	43665.5	12300001	Yes
8	169.5	1494.0	8.385	2.5	24623.5	6150001	Yes

Table 5. Indiscernibility of information table

IND A	IND B	IND C	IND D	IND E	IND F
X_1	X_1	X_1	X_1	X_1	X_1
X_2	X_2	X_2	X_3	X_3	X_4
X_3	X_5	X_7	X_5	X_6	X_5
X_4	X_6	X_8	X_7	X_8	X_8
X_5	X_3	X_3	X_2	X_2	X_2
X_6	X_4	X_4	X_4	X_4	X_3
X_7	X_7	X_5	X_6	X_5	X_6
X_8	X_8	X_6	X_8	X_7	X_7

Elementary set D

$S_7 = \{X_1, X_3, X_5, X_7\}$ (10)

$S_8 = \{X_2, X_4, X_6, X_8\}$ (11)

Equivalence set D

$S_7 U S_8 = \{\{X_1, X_3, X_5, X_7\}, \{X_2, X_4, X_6, X_8\}\}$ (12)

Elementary set E

$S_9 = \{X_1, X_3, X_6, X_8\}$ (13)

$S_{10} = \{X_2, X_4, X_5, X_7\}$ (14)

Equivalence set E

$S_9 U S_{10} = \{\{X_1, X_3, X_6, X_8\}, \{X_2, X_4, X_5, X_7\}\}$ (15)

Elementary set F

$S_{11} = \{X_1, X_4, X_5, X_8\}$ (16)

$S_{12} = \{X_2, X_3, X_6, X_7\}$ (17)

Equivalence set F

$S_{11} U S_{12} = \{\{X_1, X_4, X_5, X_8\}, \{X_2, X_3, X_6, X_7\}\}$ (18)

The next phase of discussion is set approximation. For set approximation, we mean finding the relationship between condition attributes and decision attributes for the rough set information. The condition attributes refer to the parameters while the decision attributes refer to the decisions allocated to the set of parameters. Additional information concerning set approximation is the lower approximation that concerns the definite objects belonging to the set. Besides the term, the upper approximation is relevant in this case as it refers to the elements that likely belong to the considered group. Similar to how we obtained associated values of indiscernibility we will do the same for decisions. In this case, we extract the YES term which is items 1,3,4,7 and 8. This is expressed as:

Decision X={x: decision (x) =YES} (19)

At this stage the set of elements obtained from the application of Equation (19) will be used to establish the lower approximation and the upper approximation by finding the association between the decision attribute and condition attributes via its indiscernibility (Equations (20) and (21)). At this stage, we are entering the aspect of the lower approximation. To explore this aspect, consider the right-hand side of Equation (20) which is the YES decision. This right hand of equation 20 will now be compared with our indiscernibility set. When considering a set of lower approximations, the single element should emerge with an indiscernibility set. Furthermore, since there are no single elements in our indiscernibility set to associate with our decision set lower approximation is equal to zero. The lower approximation is denoted as AX as shown in Equation (22).

Parameter A = $\{X_1, X_3, X_4, X_7, X_8\}$ (20)

IND A = $\{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\}$ (21)

AX = 0 (22)

However, to achieve the upper approximation which is to ascertain the possible answer to the YES decision attribute, we compare the different elementary sets in our indiscernibility set to find replicated values in our decision set. This results in obtaining the sets in Equation (23) as all sets have replicas in the decision set. These are labeled as possible answers to the YES decision. The upper approximation is denoted as AX in Equation (23). After this stage, the next interesting thing to do is to proceed to find the boundary region. A boundary region has a frontier that separates the definite and non-definite answers to obtain rough or vague sets. Notice that the set approximation will be done for each parameter, but at present, Equations (21), (22), and (23) are for parameter A.

AX = $\{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\}$ (23)

Therefore, similar equations need to be developed for parameters B, C, D, E, and F. The boundary region contains the vague or possible answer set to the YES decision which is obtained by subtracting the lower approximation from the upper approximation as illustrated in Equation (24).

$$BR = \{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}- \{0\}\}$$
$$= \{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\} \quad (24)$$

OR = U-AX

Here BR is the abbreviation of the boundary region. Next, the outside region represented as OR is found. This is the difference between the universal set which contains all elements ever considered for all the subset minus the upper approximation entities. This is represented in Equation (25). The above discussion is for the YES decision of parameter A. However the NO decision for parameter A needs to be examined closely. For the NO decisions, we have elements X2, X5, and X6 as in Equation (26) to be compared with the equivalence or indiscernibility set in Equation (27) of parameter A to obtain the upper and lower approximations. The next step is to find the lower approximation which is done by comparing a single or definite answer set of elements associated with YES decision attributes.

$$OR = \{X_1\},\{X_2\}\{X_3\}\{X_4\}\{X_5\}\{X_6\}\{X_7\}\{X_8\} - \{\{X_1, X_2, X_3, X_4\},\{X_5, X_6, X_7, X_8\}\}= 0 \quad (25)$$

Decision X = {x: decision (x)=NO}

Parameter A = $\{X_2, X_5, X_6\}$

IND A = $\{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\}$

AX = 0

AX = $\{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\}$

BR = $\{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\} - \{0\}\}$

= $\{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\}$

OR = U-AX

OR = $\{\{X_1\},\{X_2\}\{X_3\}\{X_4\}\{X_5\}\{X_6\}\{X_7\}\{X_8\}\} - \{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6, X_7, X_8\}\} = 0$

The findings of this study underline the considerable position of rough set theory in the discovery of patterns hidden in vehicle emission data. This helps the logistic manager to enhance efficiency and the quality of understanding of the logistic network and delivery system that is managed. Besides, the pattern of vehicle emissions from the exhaust of delivery vehicles in the packing industry assists us in gaining insights into the data and offers additional meaning to the vehicle emission data. As such, the derived results show that there are no discernible patterns or rules that distinguish between "Yes" and "No" decisions. The same set of rows is present in both the lower and upper approximations for each decision. This understanding, in strong terms, highlights the substantial effect of the rough set theory set theory in establishing the pattern hidden in the vehicle emission data. It shows the crucial requirement of the pattern hidden in the emission data for further decisions on the deployment of resources under control for vehicle emissions. Our findings are at variance with Benrajesh and Johnrajan (2019), which have addressed the quantitative optimization of vehicle emission parameters.

5. CONCLUSION

In this article, a rough set method is proposed to monitor the vehicle exhaust emissions produced by the logistics network and delivery system in the parking industry in India. In this dataset, the rough set analysis indicates that there are no discernible patterns or rules that distinguish between "Yes" and "No" decisions. The same set of rows is present in both the lower and upper approximations for each decision. Keep in mind that rough set analysis becomes more informative and valuable when dealing with larger and more complex datasets. It is also valuable when considering multiple condition attributes simultaneously. In this particular dataset, the small size and the nature of the data may not reveal significant patterns or insights using rough set theory. The method of rough set illustrated in this work was shown as feasible for the packing industry analyzed in India. The case data is drawn from India, which is a fast-growing economy, classified as a developing country. However, other developing countries could benefit from the application of the method. Moreover, this method requires limited information for its analysis and implementation in the industry. To extend the present framework, the rough set method could be merged with other methods such as the multicriteria methods of VIKOR, PROMETHEE I, and II (see Ighravwe and Oke, 2017; Odusoro and Oke, 2021). The new methods may provide more insights that could be obtained in the analysis of the vehicle emission problem in the future.

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