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Combined Application of CRITIC and Back Propagation Neural Network Prediction Method for Vehicle Emission Parametric Evaluation in Logistic Networks and Distribution Systems

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ABSTRACT

Logistic network and distribution services in the packing industry generate vast amounts of vehicle emissions, which are difficult to control due to the lack of scientific guidance. This paper predicts the emissions from vehicles engaged in logistic networks. The CRITIC (Criteria Importance Through Inter-criteria Correlation) method is integrated with the backpropagation neural network (BPNN) to analyze the input parameters of the emissions process from vehicles plying roads in the packing industry. The packing industry transports goods in packages and delivers them to customers in a road network. The application of the integrated CRITIC-BPNN method is demonstrated by using the dataset of a packing industry in India, obtained from the literature. The results revealed how the packing industry can translate its environmental control strategy into a parametric framework, yielding diverse outputs to assist in selecting optimal decisions. The proposed method exhibits unique characteristics. (1) It emerges as the first decision-making tool for objective criteria-based vehicle emission process control and could serve as a tool for logistics planning. (2) It employs integrated ideas of multi-criteria analysis and neural networks. (3) Objective and optimal emission analysis decisions are advanced through an analysis of multi-criteria tools. By employing the CRITIC method, the conflicting objectives of the emission process are successfully tackled and synchronized objectively to arrive at robust weights used in the back propagation neural network method for the final prediction. Moreover, the neural network method uses intelligence to gather data and translate it into usable forms to predict vehicle emissions.

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1. INTRODUCTION

The growing customer demand for quantities and varieties of products in society has triggered environmentally-conscious logistics networks and distribution systems (Sun and Li, 2021). To reduce the obstructions caused by this movement, it is crucial to optimize the logistics and distribution frameworks and establish green promotion strategies (Atmayudha et al., 2021; Bennani et al., 2022; De Souza et al., 2022; Eslamipoor, 2023). However, the strategies fail in their implementations. For example, installing emission control facilities in delivery vehicles fails as small-scale industries are not capable of installing such facilities in their delivery vehicles (Dutta and Chavaparit, 2023). Also, medium and large companies are troubled by the frequency of replacements of these facilities, as such replacement negatively impacts the profit of the packaging industry. Moreover, the suggested control measure of reducing the number of delivery vehicles by the packing industry also fails because of the inability of a small fleet of vehicles to satisfy the logistics and distribution demands of the packing industry. Among all the alternative options, the use of quantitative emission metrics for control in agreement with environmental standards is promising (Karaman et al., 2020; Stekelorum et al., 2021). Thanks to their ability to assist in gaining insight into the critical characteristics of vehicle emissions, such as emission rates, engine condition, vehicle maintenance, skill and qualifications of vehicle drivers, etc., with objective data, one can evaluate the environment's and vehicle's emission performance and embark on more informed environmental production decisions (Maduekwe and Oke, 2022; Maji et al., 2023).

Moreover, the intrinsic non-linear attributes of the VEE process critically obstruct the traditional approach to establishing parameters. Therefore, equipment grid mathematical models with diverse variables and application potentials have been broadly used in establishing the parameters of the VEE process. For example, Stokic et al. (2023) assessed vehicle exhaust emissions for commercial vehicles under varying operating situations using a bilinear interpolation model. Besides, the chassis dynamometer experiment coupled with a kinetic model was used to establish the emissions from the exhausts of gasoline vehicles.

Furthermore, maintaining a clean air environment globally is fraught with complicated problems (Ajayi et al., 2023). One of these problems is created by the packing industry that controls delivery vehicles in logistics networks and delivery systems. These vehicles emit dangerous gases (greenhouse gas emissions) such as sulfur compounds, nitrogen dioxide, and carbon monoxide (Gao et al., 2022). When inhaled, these gases are responsible for respiratory problems among many inhabitants of a society. To control this problem, manufacturers have, over the years, engaged in engine modifications, which are expensive to make. This could only be feasible in large-scale organizations where funds are available to purchase highly effective vehicles that produce few emissions to the environment. In this case, the small and medium-scale industries cannot afford the purchase of such vehicles. The other approach to controlling these emissions is to enact laws regulating the use of vehicles that emit pollutants above the standard thresholds (Shiet et al., 2023; Woo et al., 2023; Di et al., 2023). This approach does not seem to help the small-scale enterprises in the packing industry, as they are forced to abandon their vehicles, which do not meet the standards. However, the third and most feasible option is to propose methods that evaluate and control vehicle emissions. Consequently, over the years, studies have been conducted on vehicle exhaust emission evaluation (Keuken et al., 2012; Chauhan et al., 2019; Tong et al., 2020; Ngo, 2022; Hata et al., 2022). In this paper, the first integrated method of CRITIC back propagation neural network, named the CRITIC-BPNN method, which objectively evaluates the parameters of vehicle exhaust emission in the packing industry, is presented.

Besides, in the packaging industry, decision-makers are confronted with managing and using greenhouse gas emission information to control environmental air quality (Demir, 2015). Unfortunately, the literature lacks methods that fuse contemporary multicriteria methods, including CRITIC and entropy. This paper aims to address this research gap by proposing a decision-making tool that combines the CRITIC method and the backpropagation neural network approach.

The CRITIC method was first deployed to evaluate the weights of the parameters as they are classified as beneficial and non-beneficial. Normalization routines for the parameters, standard deviations, a symmetric matrix, correlation coefficients, and the objective weights of the parameters are established. The obtained weights are fed into the input layer of the backpropagation neural network. Signals are transferred to the hidden layers, while the transfer functions and weights are used to provide information for the output of the neural network. The primary value and uniqueness of the present study is that it positions itself as the first article to objectively predict the parametric values of vehicle exhaust emissions. This paper helps to establish the interaction between multicriteria and neural network methods. It raises our level of understanding in the emission control area. In the Indian packing industry, few investigations have been made on predicting the exhaust emissions from vehicles (Chhabra et al., 2017; Croitoru et al., 2020). By focusing on the Indian environment and the logistics network section of the country, this study aims to offer novel insights and contribute to the insight into logistics dynamics.

The principal objectives and the novelties that this study claims are stated as follows:

1. A backpropagation neural network based on the vehicle exhaust emission process framework is constructed and trained. This has a strong positive influence on the accuracy and stability of the established parameters compared with other procedures.
2. The BPNN method used in this article demonstrates comparable convergence speed to establish the vehicle exhaust emission process parameters when compared with metaheuristics such as particle swarm optimization.

3. The results of the simulation obtained from the analysis revealed that the BPNN successfully established the parameters of the emission process, revealing relatively high accuracy, stable performance, and fast convergence.

Moreover, the motivation for this work is to utilize the BPNN to predict vehicle exhaust emission parameters, including the output, which is Z. The input parameters comprise A to F. The contributions of this work could be explained as follows:

1. This research evaluates the parameters of vehicle exhaust emission on roads, in the Indian Scenario, and obtains data from the packing industry using the backpropagation neural network model. The BPNN model was used because it has the ability to predict environmental parameters.
2. This research is the first to utilize artificial neural networks to predict vehicle exhaust emissions within the packaging industry in the Indian Scenario. The predictive error of the model is within a reasonable value range. The model was trained on the data from the packing industry across a specific road in the Indian Scenario.
3. This work utilizes an objective method called CRITIC to evaluate the weights of the vehicle emission parameters for the computation of the predicted parametric values of vehicle emissions in the industry.

Given the dynamics of the vehicle emission process in question, this work aims to first obtain objective values of parameters, which will be used to represent the conflicting nature of the objectives in an analysis framework. Moreover, despite the efficiency of the artificial neural networks, no studies have reported the prediction of vehicle exhaust emission in the packing industry of the Indian environment within the framework of logistic networks. This presents a significant research gap in the context of the unique emission discharge to the environment by vehicles that ply these roads (Zamboni et al., 2009). Thus, a dataset obtained from an industry operating in the packing area of India, available as secondary data, is used in the present study. Considering the Indian environment as a fast-growing developing country, this work aims to offer valuable insights for logistics managers and environmental regulators in India and other developing countries. This work also contributes to a broader understanding of the emission prediction of the under-researched packing industry in India. In addition, this research introduces a new structure by integrating the CRITIC method with the backpropagation neural network. Data was applied to the integrated method with respect to the attributes of the Indian supply chain industry (Liu et al., 2022; Vo and Nguyen, 2023). By implementing the proposed integrated method, the study attempts to enrich the predictive accuracy of vehicle emission methods, stimulating a reliable calculation procedure and an improved understanding of the negative contributions of vehicular emissions to the environment.

2. LITERATURE REVIEW

The problem of vehicle emission prediction in logistic and distribution networks falls in the category of those that could be solved using decision-making tools and artificial neural networks. Hence, the literature along these two aspects is discussed in the present section to justify the originality of the study. The literature review is reviewed comprehensively to reveal the newness of the problem discussed in this work, justify the methodology, and also the results emanating from the application of the methodology. The gap in research is shown by revealing the present and projected state of knowledge in the field. Furthermore, the literature review is conducted first on neural networks in vehicle emissions studies and is discussed afterwards.

2.1. General Review

Ajayi et al. (2024) analysed how engine features of vehicles influence. The emission of vehicular air pollutants from a fleet of 88 vehicles using gas analyzers was considered. It was concluded that minibuses and cars deliver carbon monoxide from their engines to the environment, but trucks and large buses deliver oxide compounds from their diesel engines. Compared with the present study, the experimental study adopted by the reviewed article is cost-intensive and can only be adopted in situations where the cost can be afforded. In contrast, without expending much money, the present method could be adopted even with sparse data. Besides, the results given in the present study are objective. Pilla et al. (2022) proposed a structure to approximate NOx emission levels across the vehicle system operating conditions. The framework proposed is a deep neural network that triggers the development of a tailpipe NOx model and an engine-out NOx, which predicts emissions from heavy-duty vehicles, namely the NOx emission. It was concluded that the DNN-NOX emission detection method was effective to detect fault.

The integration of fuzzy knapsack dynamic programming and EDAS methods in monitoring vehicle emission parameters, in the packing industry, was first proposed by Agada et al. (2024a). The method demonstrated the significance of parameters B and E (packing units sold and carbon dioxide equivalent of packing materials, respectively) in achieving minimized emissions from the test vehicles. Moreover, Agada et al. (2024b) devoted their study to investigating the parametric evaluation of vehicle emissions through the joint PROMETHEE, 0/1 knapsack dynamic programming method. The results yielded feasible solutions for the alternative methods considered. These are the trapezoidal and triangular fuzzy extent synthetic combined with PROMETHEE II, and the triangular-based fuzzy geometric mean combined with PROMETHEE II methods. Agada et al. (2023) predicted emission patterns from vehicles in the packing industry using rough set theory. The outcome of the study is the optimized emissions and costs from the packing industry investigation.

2.2. Neural Network in Vehicle Emissions

Zhou et al. (2008) deployed a two-phase method on emission prediction and optimization. The first phase of the study uses the neural network model to analyse catalytic converter activities and engine operations. An optimization model is the principal framework of the second phase of the research. The optimization tool established the engine parameters, which are optimal to enhance fuel efficiency and reduce emissions. It was reported that the approach is economic, which is in the same domain as Guo et al. (2010). Compared with the present study, predicting emissions from vehicles is reviewed in this reviewed study and the present work. However, the characterization of the parameters was downplayed therein. Yet there is a need for an objective way of calculating the weights of the neural network, such as to provide a robust framework for vehicle emission reduction. Unfortunately, this is missing in the reviewed study.

Kim and Lee (2010) proposed a neural network–oriented method to enhance emission quantity approximation and accuracy. It was reported that the neural network method outperformed the multiple regression model using the mean absolute percentage error. It was declared that the additional tool provided a look-up table that aided the estimation of emissions by avoiding the training and development of the artificial neural method. The common element of the article and the present work is the prediction of parameters. However, in their work, the objective determination of weights was ignored despite its utility in enhancing the robustness of calculations of the final outputs from the neural networks.

Taheri-Garavand et al. (2022) proposed a new artificial neural network-oriented method with graphene quantum dots nanoparticles on the performance and emission attributes of the engine established. The conclusion is that the brake power and engine torque increased as the graphene quantum dots plus E to 10% of waste fish oil biodiesel. While the similarity of the study with the present study lies in the application of a neural network, the weights of the network were given from the traditional account of estimations. However, an objective weight declaration is superior to such estimations. Thus, there is a gap in knowledge in introducing objective weights into the evaluation and prediction of exhaust emissions using the neural network. The gap could be bridged by introducing the CRITIC method in this regard.

Niroomand and Bach (2024) integrated machine learning methods to predict CO2 emissions from vehicles. The machine learning methods employed in the emission prediction are the semi-supervised deep fuzzy C-means, support vector regression, and random forest. The methods were used to examine the inputs from an engine. Compared to the present study, the machine learning methods, despite providing a basis for management decisions on emission control, are unable to disclose how conflicting objectives in the emission process control could be tackled. CRITIC could be employed to objectively unite the criteria of the emission process.

2.3. Decision-making tools in emission studies

Bortnowski et al. (2024) developed a decision tree-oriented toxic emission predictive method using the operational parameters of the engine. In addition, the Bayesian optimization method was deployed to fine-tune the hyperparameters of the method. It was reported that the method displayed satisfactory accuracy. Compared with the present study, a decision tree is part of the global tools of decision-making. However, the study omits the artificial intelligence of which neural network is a member of the group of tools under artificial intelligence. This omission limits the robust potential outcome of the study. Thus, it is essential to apply the CRITIC method and the neural network method when predicting emissions from vehicle exhausts.

Huang and Zhu (2024) proposed a two-stage planning method that optimizes the parameters of the road traffic network using the IS-APCPSO algorithm that was developed on the Internet of Things framework. It was confirmed that the total vehicle emissions produced using the method were reduced compared to using the traditional method. Although the contribution is useful in optimizing the road network emission parameters, there is a gap in that the optimization figures may not be taken as an objective prediction since it contains no objective methodical component, such as the CRITIC method. This gap requires urgency to bridge it.

In summary, the above studies reviewed collectively illustrate how versatile and applicable the back propagation neural network is in improving the predictive ability of managers in the packing industry. This work informs strategy emission control decisions across diverse domains the work underscores the significance of advancing the neural network algorithm and data-motivated insights to pursue more effective analysis of the exhaust emission process and decision-making on emissions.

3. METHODOLOGY

There are several aspects of the vehicle emission parametric evaluation problem. These could be explained regarding its dimensions, how to measure it empirically, and how to predict it. Concerning its dimensions, this concept may be viewed in terms of the vehicle characteristics, operational parameters, vehicle-specific power, pollution categories, and environmental and infrastructure situations (Yang et al., 2021). Vehicle characteristics entail fuel consumption, emission control technology, fuel category, engine age, weight, and capacity. On the empirical methods to measure vehicle emission parameters, the key categories include the roadside and remote sensing technologies. These are primarily the use of remote sensing devices and the tunnel study measurements. The second category is the on–board measurement method, which entails the use of on–board diagnostic data logging and the portable emission measurement system. The third category is the laboratory-based empirical methods, consisting of the use of dynamometers and engine bench testing. The fourth type is data processing and modeling, which entails emission maps and data-driven modeling. The find category is the parametric evaluation methods, which could be further grouped as the power-oriented, moving average window, and vehicle-specific power method. Building on the insights given above, the results of the study are based on the data collected from the field study and hence do not

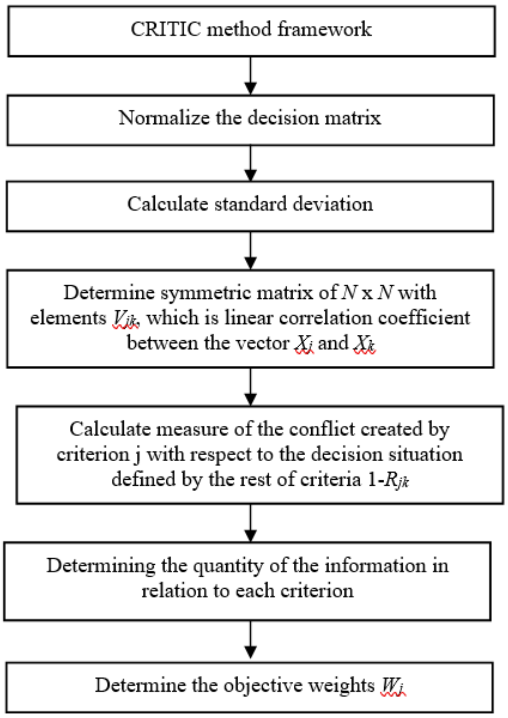

Figure 1. Research scheme for CRITIC method

consider most methods mentioned earlier because of the data availability constraints. Moreover, predicting the parameters in this study involves the use of the BPNN method on a CRITIC methods platform. The BPNN was trained on the field data collected in an earlier literature study.

In this study, the CRITIC method was used to estimate the weights of vehicle emission parameters, which were introduced into the framework of the BPNN prediction model (Figure 1). The BPNN model is used for the final calculations of the predictive values of the parameters of the vehicle emission process in the packaging industry (Figure 2). Thus, the description of the methodology is as follows:

The normalization of the decision matrix is indicated as Equation (1).

$$X_{ij(normalised)} = (X_{ij} - X_{worst})/(X_{best} - X_{worst}) \tag{1}$$

where,

$X_{ij(normalized)}$ = the normalized value of the parameter under consideration.

X_{ij} = the raw value of the parameter.

X_{worst} = the worst value of the parameter.

X_{best} = the best value of the parameter.

The standard deviation of the normalized values under each parameter is given as Equation (2).

$$\sigma_{normalised} = \sqrt{\frac{\left(\sum X - \mu\right)}{n}} \tag{2}$$

where, $\sigma_{normalised}$ is the normalized value of the standard deviation.

The correlation between one parameter and the other is calculated using Equation (3):

$$r = \frac{\left(\sum (X_i - \bar{X})(Y_i - \bar{Y})\right)}{\sqrt{\sum (X_i - \bar{X})^2 \sum (Y_i - \bar{Y})^2}} \tag{3}$$

where,

r = the correlation coefficient.

X_i = values of the X variable in a sample.

$\bar{X}$ = the mean of the values of the variable.

Y_i = values of the Y variable in a sample.

$\bar{Y}$ = the mean of the values of the variable.

The measure of conflict created by each parameter concerning the decisions is calculated using Equation (4).

$$M_c = \sum \left(1 - r_{jk}\right) \tag{4}$$

where, M_c is the measure of conflict.

In backpropagation, the goal is to reduce the cost function that features as a member of the neural network deviates from its actual values. It evaluates the error occurring when the output predictions are compared with the actual outputs. By adjusting the weights and biases of the networks, the cost function is reduced. However, the gradient of the cost function establishes the degree to which the adjustments are made regarding parameters such as bias, activation function, and weights. Next is an explanation of the need for an activation function in neural networks. The reason for the activation function is best explained by considering the effect of not having activation functions in our neural network analysis. To start with, it is agreed that instituting the activation function during the forward pass computations of the backpropagation neural networks yields extra computations. But one will appreciate that it is worth it when you experience that all layers behave alike without an activation function. So it is difficult to achieve results when one is treating a complicated task, and the use of a linear regression model would have been a good fit to solve this problem of obtaining similar results for layers. Notice that what the linear regression model will do is to disallow every neuron to be linearly transformed using biases and weights. In this situation, irrespective of the number of hidden layers that are appended to the neural

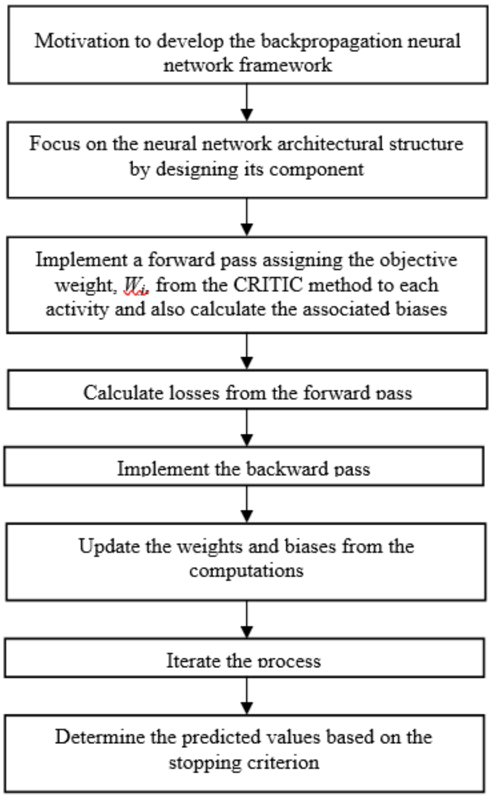

Figure 2. Flow process for the implementation of the CRITIC method-based back propagation method

network, the composition of any two linear functions, which are linear functions themselves, would behave likewise.

In the backpropagation neural network, there are two passes: the forward and backward passes. The forward pass is characterized by a situation where the researcher commences by propagating the vehicular data inputs to the first layer (input layer). The process entails going through the hidden layers and progressing until the network's predictions are evaluated as the output layer is touched. The final effort is to evaluate the network error, which is the difference between the actual values of the parameters and the values of the predictions in the network analysis. Another name for the forward pass is forward propagation. At the intermediate points in the network, the input, hidden, and output layers, and the values of predictions, including weights, are stored for further reference and evaluations. We visualize weights in neural networks as actual values, which are assigned to a feature or an input. They represent the essentials of the corresponding feature in their efforts to predict the final output. However, the backward pass, known as backpropagation, operates as an adjustment of weights to achieve the difference between the actual and predicted outputs. Neural network actions are broadly classified as training and predictions. The training aspect of neural networks computes weights. Training commences by instituting a group of random weights and then adopting the backpropagation scheme to update weights. Efforts are made to weigh and concurrently allocate inputs to outputs in the scheme of analysis.

3.1. Design Network Architectural Structure

Define the structure of your neural network, including the number of layers, the number of neurons in each layer, and the connections between them. Assign initial weights to the connections between neurons. These weights will be updated during the training process.

Determine and execute a forward pass of the objective weights, w_j

Start with an input data point and pass it through the network layer by layer. For each neuron, compute the weighted sum of its inputs (including bias), and then apply the binary sigmoidal activation function to get the neuron's output.

$$a_j = \sum (W_{ij} \times X_j) \quad (5)$$

$$y_j = F(a) = \frac{1}{(1 + e + a_j)} \quad (6)$$

3.2. Calculating Losses

Compare the network's output (prediction) with the true target value. Calculate the loss. The choice of the loss function depends on the specific problem. For binary classification, the cross-entropy loss is commonly used.

$$\text{Error} = \text{Target value} - \text{Computed value}$$
$$= E_{target} - E_{computed} \quad (7)$$

3.3. Execute Backward Pass

Calculate the gradient of the loss concerning the network's weights and biases. This is done by applying the chain rule of calculus. The gradient indicates the direction and magnitude of the change needed in the weights and

Table 1. Factors and levels (Benrajesh and Rajan, 2019)

Level	A	B	C	D	E	F
Level 1	52	127	0.77	1.5	5581	1
Level 2	171	1494	16.00	2.5	43666	12300000
Level 3	287	2861	30.34	3.5	81750	24600000
Best	287	2861	30.34	1.5	81750	1
Worst	52	127	0.77	3.5	5581	24600000
	B	B	B	NB	B	NB

Note: B – beneficial; NB – Non-beneficial

biases to minimize the loss.

$$\delta_j = O_j(1-O_j)(t_j - O_j) \text{ for output unit} \quad (8)$$

$$\delta_j = O_j(1-O_j)\sum k\delta_k W_{kj} \text{ for hidden unit} \quad (9)$$

$$\Delta W_{ji} = \eta \delta_j O_i \text{ for weight} \quad (10)$$

$$\delta_Z = Z_{(1-Z)} - Z_{(target-Z)} \quad (11)$$

$$\delta_{Y1} = Y_1(1-Y_2)\sum k\delta_z W_1 \quad (12)$$

$$\delta_{Y2} = Y_2(1-Y_2)\sum k\delta_z W_2 \quad (13)$$

where,

ŋ = the learning rate.
δ = the error term.
O_i = the output of the i^{th} term.
t_j = the correct target output for unit j.
δ_j = the error measure for unit j.
k = the number of the output unit.

3.4. Evaluate Prediction Based on Stopping Criterion

Use an optimization algorithm (e.g., stochastic gradient descent) to update the weights and biases of the network based on the calculated gradients.

3.5. Iterate The Process

Repeat the forward passes, loss calculations, backward passes, and weight updates for multiple iterations (epochs). These iteratively improve the network's performance.

3.6. Update your weight and biases

Pass the new data through the trained network, and based on the output of the final layer's neurons (which are activated using the binary sigmoidal function), make binary classification decisions using a threshold.

4. RESULTS AND DISCUSSIONS

In this work, a back-propagation neural network model is applied to the parametric settings defined initially by the Taguchi design for greenhouse gas emission in the packaging industry. Using this data as inputs, an output, which is an optimized quality of greenhouse gas emission, represented as Z, is proposed. The inputs are labeled from A to E. The parameter A is the Revenue attained in the packing industry in the reference year (Million Dollars). It is chosen as a parameter of interest because it serves as a baseline with which the capital to invest in costly technologies for monitoring the performance of the industry is compared. The parameter B is the packing units sold. Parameter B is important as it directly impacts material usage, transportation efficiency, and fuel consumption associated with logistics. Moreover, the packing units per delivery vehicle are critical in reducing emissions from the perspective of reduced trips and fuel. The parameter C is the compound annual growth rate. It is used as a critical parameter to assess greenhouse emissions based on the understanding that the last-mile delivery is a major source of emissions.

Focusing on it to control greenhouse emissions through monitoring its growth rate provides substantial data to negate its impact on sustainability in the industry. Parameter D is the materials used for packing. This parameter impacts the overall carbon footprint of the product lifecycle and is therefore considered important. Parameter E is the quality consumed. Measuring and reducing the quantity of packaging materials moved in delivery vehicles is central to reducing greenhouse emissions. The key reason is that the volume and mass of packaging transported on roads have a direct influence on the fuel consumption and transportation efficiency. Parameter F is the carbon dioxide equivalent. This parameter is significantly placed in the domain of measuring and analyzing the greenhouse gas emissions obtainable in the product's life cycle.

4.1. CRITIC Method

The methodology employed to analyze the data is in two phases. The first phase that uses the critic method, initiated from Table 1, contains the factors and levels that are provided in Benrajesh and Rajan (2019).

With this data, a distinction between beneficial and non-beneficial is made. Accordingly, ABC and E are beneficial factors while D and F are non-beneficial factors. Then we progress to finding the best and worst values for each parameter. These are respectively 287 and 52 for A, 2861 and 127 for B, 30.34 and 0.77 for C, 1.5 and 3.5 for D, 81750 and 5581 for E, 1 and 2.5E7 for F. Next, the normalization of the decision matrix is conducted using Equation (1). Notice that the basic reason for distinguishing between beneficial parameters and non-beneficial parameters is to establish a variation between the values. Beneficial parameters select the highest values in Table 1 as the best values and their least values as the worst values, while the non-beneficial parameters select the least values in Table 1 as the best values and the highest values as the worst values. For example, parameter A is a beneficial parameter, and it is expected that the best value will be the highest one at level 3 and

Table 2. Normalized decision matrix

Level	A	B	C	D	E	F
Level 1	0	0	0	1	0	1
Level 2	0.5064	0.5	0.5150	0.5	0.5000	0.5
Level 3	1	1	1	0	1	0

Table 3.Standard deviation

Level	A	B	C	D	E	F
Level 1	0	0	0	1	0	1
Level 2	0.5064	0.5	0.5150	0.5	0.5000	0.5
Level 3	1	1	1	0	1	0
Standard deviation	0.5000	0.5	0.5001	0.5	0.5	0.5

Table 4. Symmetric matrix

Parameter	A	B	C	D	E	F
A	1.0000	1.0000	1.0000	-1.0000	1.0000	-1.0000
B	1.0000	1.0000	0.9998	-1.0000	1.0000	-1.0000
C	0.9999	0.9998	1.0000	-0.99985	0.9998	-0.9999
D	-1.0000	-1.0000	-0.9999	1.0000	-1.0000	1.0000
E	1.0000	1.0000	0.9998	-1.0000	1.0000	-1.0000
F	-1.0000	-1.0000	-0.9999	1.0000	-1.0000	1.0000

the worst value will be the lowest value at level 1. The reverse is the case with parameter D, which has the best value being the lowest value at level 1 and its worst value being the highest value at level 3. We applied equation 1, which is for the normalization of the values in Table 1, to generate values between 0 and 1 in Table 2.

Consider parameter A, for instance, the value at level 1 is 0. However, the highest value, which is at level 3, is 1. The value at level 2 is calculated as 0.5064. Notice that in the multi-criteria domain, there exist two weight determination methods. The first type is called the subjective weight determination approach. The usual inputs into the subjective method are the evaluations given by the key stakeholders within the company. In this case, the three decision-makers who could evaluate the values of the weights are the general manager, the supply chain manager, and the financial director. When inputs from these people are used to evaluate the weight, it is called a subjective approach, and methods that could be classified as such include the analytical hierarchy process. Subjective methods are avoided in the present work. However, we are employing the critical method, which is an objective method that does not require the input of decision-makers. Now, an important part of the CRITIC method is to obtain the standard deviation of the normalized values under each parameter, Equation (2) (Table 3).

This shows how spread out the data from each parameter is. Notice that the standard deviation (Equation 2) relates the population standard deviation to the size of each value by the highest and lowest standard deviation, considering all the parameters A to F. A value of 0.5 was obtained for each parameter as a standard deviation (Table 4).

The next task is to develop a symmetric matrix to generate Table 4 of parameters A to F. In determining the symmetric matrix, the first step is to input 1 at each location where a parameter intersects itself. That is, where A and A intersect, a value of 1 is placed therein. Notice that for Table 4, there are the left and right sides. Next, obtain the correlation between the parameters. Consider calculating the parameter along row A, but B along the column. For this case, Equation (3) may be used. However, the correlation function in Microsoft Excel is deployed to establish the correlation coefficient of the data. The correlation of ranges of parameters in rows against columns from Table 3 is found. The next step is to measure the conflict created by each parameter concerning the decisions using Equation (4). Equation (4) is obtained by subtracting the correlation value earlier obtained from 1 for each value in Table 4. To illustrate this, consider row A and its intersection with column D in that cell. The value of 1.99997 is obtained. This is traced backwards to the correlation value in the previous table (Table 4), which gives -1.0000. Then subtracting the negative of this value from 1 gives 2.0000. The same approach is used to compute other values in Table 5.

An important point to mention is that the values obtained on the left-hand side and lower part of the diagonal- are the same as those obtained on the right-hand side of the upper part of the diagonal. Having obtained the measure of conflict along each row, the sum is obtained. For example, the values at the intersection of row A and columns A, B, C, D, E, and F are 0, 2.7E-5, 5E-5, 1.99997, 2.7E-5, and 1.99997, which gives 4.00005. The next step is to determine the quantity of information about the criterion of standard deviation and correlation. This is done by multiplying the standard deviation by the sum of measured conflict (Table 6).

Consider parameter A, the standard deviation, conflict value, and their product are 0.5000, 4.00005, and 2.00008, respectively. This production is called information quantity. The next phase of the work is to determine the objective weights, which is to find the proportion of the information quantity of each parameter to the total value of information quantity for all parameters. These weights

Table 5. Measure of conflict

Parameter	A	B	C	D	E	F	$\sum(1-r_{jk})$
A	0.0000	2.72E-05	5.01E-05	2.0000	2.71E-05	2.0000	4.0001
B	2.72E-05	0.0000	0.0002	2.0000	2.87E-11	2.0000	4.0002
C	5.01E-05	0.0002	0.0000	1.9998	0.0002	1.9998	4.0001
D	2.0000	2.0000	2.0000	0.0000	2.0000	0.0000	7.9998
E	2.71E-05	2.87E-11	0.0002	2.0000	0.0000	2.0000	4.0002
F	2.0000	2.0000	1.9998	0.0000	2.0000	0.0000	7.9998

Table 6. Quantity of information

Parameter	δ_j	$\sum(1-r_{jk})$	C_j
A	0.5000	4.00005	2.0001
B	0.5000	4.000178	2.0001
C	0.5001	4.00005	2.0003
D	0.5000	7.999822	3.9999
E	0.5000	4.000178	2.0001
F	0.5000	7.999822	3.9999

Table 7. Objective weights

Parameters	δ_j	$\sum(1-r_{jk})$	C_j	W_j
A	0.5000	4.0001	2.0001	0.1250
B	0.5000	4.0002	2.0001	0.1250
C	0.5001	4.0001	2.0003	0.1250
D	0.5000	7.9998	3.9999	0.2500
E	0.5000	4.0002	2.0001	0.1250
F	0.5000	7.9998	3.9999	0.2500
		Sum	16.0000	

will be used for back propagation neural network models to be used in the future. Besides, the relative weights of the parameters show us the comparative importance of one parameter to the others. In this case, the most important parameters are D and F. The least important parameters are A, B, C, and E. This result was compared with what was obtained in previous work by the same authors, where 0 1 knapsack dynamic programming was employed. In that case, parameter E was taken as the best one, which conflicts with the best one in the critic method (i.e., parameters D and F) (Table 7).

4.2. CRITIC-BPNN Method

To accomplish the backpropagation method, a network consisting of inputs, hidden layers, and output nodes is represented in Figure 3.

Backpropagation, which is sometimes referred to as the neural network tool for backpropagation of errors, is designed to evaluate errors by working backwards from the output nodes to the input nodes. It improves the accuracy of predictions in the neural network evaluation. In all, there are two nodes representing the input nodes, namely, and . Next, is the node to the left-hand side of Figure 3, while is the node to the right-hand side of Figure 3. The error change in weight is shown in Table 8.

The hidden layers of the backpropagation method are represented by and, which are from the left to the right-hand side of the neural network. Next in the structure of the backpropagation method is the output node. The hidden layer in the method allows the neural network to function. It serves as a root to break down the inputs and transform them into output.

The output of a backpropagation method

The analysis commences by finding the hidden nodes using the input values and weights from the critic method. Now we have to assign values to each node regarding what they receive, what they give out, and the weight, as well as the learning rate, with a sigmoidal activation function. The first input node X_1 receives a value of 0 from the sigmoidal activation function. This is similar to the concept of beneficial and non-beneficial in multi-criteria analysis. Next, 0 represents non-beneficial parameters, while 1 shows that it is a beneficial criterion. Next, we state what the weights are for the activities X and Y. Now, concerning the weights, four weights were selected from the critical method. These are V_{01}, V_{11}, V_{02}, and V_{12}. Notice that there are six weights obtained from the respective parameters using the critic method. These weights are 0.125, 0.125, 0.125, 0.2499, 0.125, and 0.24999 for parameters A, B, C, D, E, and F, respectively. In this analysis, we picked weights from the six different weights obtained such that their impacts on emission discharge will not be significant. This is because we are trying to minimize the emissions discharged from the process. Thus, the focus is on four weights, which are V_{01}, V_{11}, V_{02}, and V_{12}. Notice that the weights associated with non-beneficial parameters are not considered. Now the computation starts with V_{01} which is for parameter A and has a value of 0.125. In the same way, values are assigned

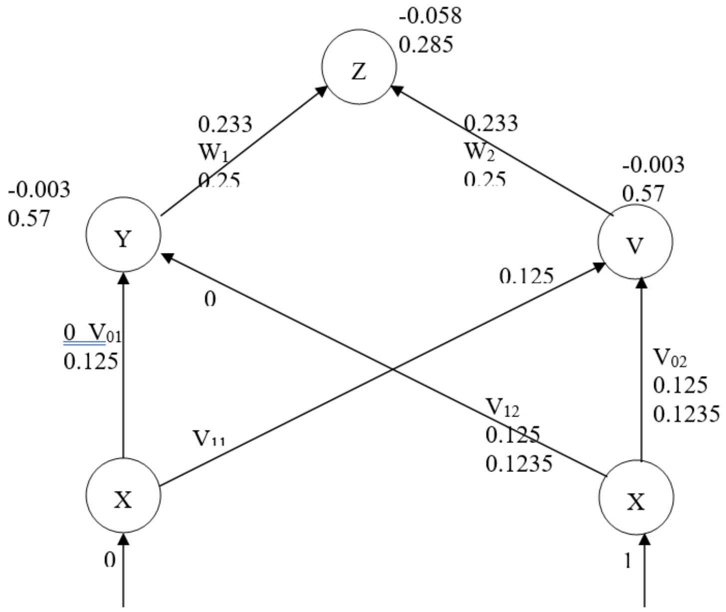

Figure 3. Back propagation neural network using binary sigmoidal activation function

Table 8. Error change in weights

Scenario	Weights	Xi	Δ	ŋ	Δweights
1	0.25	0.57	-0.058	0.5	0.233
2	0.25	0.57	-0.058	0.5	0.233
3	0.125	0	-0.003	0.5	0.125
4	0.125	0	-0.003	0.5	0.125
5	0.125	1	-0.003	0.5	0.1235
6	0.125	1	-0.003	0.5	0.1235

to V_{11}, V_{02}, and V_{12} as 0.125, 0.125, and 0.125. Notice that V_{01}, and V_{11} are the weights of the activity X_1Y_1 and the direction of movement is from the input layer X_1 to the hidden layer Y_1. Also, associated with the node X_1 is the activity X_1Y_2, which weights V_{11}. The direction of this activity is from X_1 to Y_2. This is from the input layer. X_1 to a hidden layer Y_2. Furthermore, the activity X_2Y_2 weighs V_{02}, and it flows from the node X_2 to node Y_2. Also, from the node X_2 is an activity X_2Y_1 which flows from an input layer to a hidden layer. The value of the weight on this activity is V_{12}. At node Y_1 signals are sent to node Z through the activity Y_1Z. The weight of this activity is W_1(0.25). Notice that any result we obtain for Y_1Y_2 becomes the input value of Z. Besides, there is a transfer of information from Y_2 to Z along the path Y_2Z. The weight for Y_2Z is W_2, which is 0.25. In this analysis, there is a need to state the learning rate. The learning rate is 0.5. This is so fixed because the value of 0 will be too low, and the value of 1 will be too high. However, a value in between, which is 0.5, will be moderate and is useful for this analysis. It is interesting to note that the whole process of backpropagation has both forward and backward passes. Notice that to compute Y_1, Y_2, and Z, we must apply the activation function. Now, the effort to compute the hidden layer commences with the node Y_1 to obtain a node Y_1.

In the next stage, we need to run an iteration for the backpropagation process. We continue the loop until we get the changed weight to obtain the output target of zero. The iteration is done such that we have a reduced value like that of W_1 and W_2 from 0.25 to 0.233. Also, V_{02} and V_{12} are from 0.125 to 0.1235. Based on the results, the optimal weights are the least change in weight using a back propagation neural network. We have obtained a changed weight, which will reduce the target to the minimum. Thus, arriving at the optimal value for a reduced greenhouse gas emission capacity. Furthermore, after 23 iterations, weights were obtained from the propagation method. The error was reduced from -0.28 to -0.1064 (see appendix). Thus, a significant change in weights was achieved. this change impacted on W_1, W_2, V_{01}, V_{11}, V_{02}, and V_{12} values from 0.2333,0.233,0.125,0.125,0.1235 and 0.1235 respectively to 0.09137, 0.09137,0.125, 0.125, 0.11299, and 0.11299 respectively.

These are the new predicted weights for the backpropagation neural network. These weights are to be used to rank which of the levels given in Table 1 of Benrajesh and Rajan (2019) is the most important in value, and accordingly, the following is true: W_1 and W_2 represent the weights for parameters D and F, while V_{01}, V_{11}, V_{02}, and V_{12} representing the weights for parameters A, B, C, and E, respectively. A careful study of the pattern of results was made. The results are compared with the outcome of implementing the fuzzy geometric mean (triangular) on the data by Benrajesh and Rajan (2019). The weights for parameters D and F were less than the weights for parameters A, B, C, and E. This resulted in attaching prominence values of level 3 for parameters A, B, C, D, E, and F from Benrajesh and Rajan (2019). The values are 287, 2861, 30.34, 3.5, 81750, and 24600000 for the respective parameters of A, B, C, D, E, and F.

4.3. Managerial Insights of The Study

This study allows the manager to understand the nuances and complexities of the vehicle emission parametric evaluation process and provides deeper insights from a managerial perspective in several ways. Firstly, the paper enhances vehicle emission decision-making with high accuracy. The CRITIC-BPNN model leverages the strength of both the CRITIC and BPNN methods to generate high accuracy, promoting informed decisions among vehicle managers on such issues as fuel alternatives, routes, and fleet mix. Secondly, the study provides insights into optimal resource allocation. The CRITIC component of the integrated model encourages vehicle managers to establish the key parameters in the evaluation process. This eliminates subjective bias of the manager and the team, directing efforts at the true drivers of emissions. Thirdly, this research provides practical insights into how real-time monitoring and dynamic evaluative properties of the BPNN component of the CRITIC-BPNN method could facilitate estimations and instant corrective actions. This is preferred to the current practice, which depends on static, time-concentrated evaluation schemes. Fourthly, this study provides valuable practical insights for cost reduction and green logistics. The accurate prediction of emissions helps in transitioning to green logistics from the present non-sustainable status. The implication is that it leads to minimal operational cost of the system and reduced environmental impact. This arises from optimized scheduling and vehicle routing schemes.

5. CONCLUSIONS

It is necessary to produce an accurate model of the vehicle exhaust emission (VEE) process for reliable analysis and operation. In such a situation, the unknown parameters require some estimation. Unfortunately, the intrinsic, non-linear attributes of the VEE process critically obstruct the traditional approach to establishing parameters. Consequently, to overcome these difficult obstructions, the back propagation neural network, which is founded on the artificial neural network principles, has to be suggested to establish the parameters of the VEE process. Besides, the simulation results obtained from the deployment of the BPNN to the literature data used to validate the data reveal the following: it was shown that the BPNN method exhibits accuracy and faster speed while establishing parameters.

Furthermore, the following are the conclusions emerging from the findings of this research:

1) The backward propagation allows the researcher to adjust the weights of the vehicle emission process parameters to the minimum error values. This improves the prediction of the proposed CRITIC-BPNN method.
2) The findings showed that the loss in weights of parameters D and F, which was 0.233, was reduced to 0.09136. However, the limitation of this work lies in the fact that to reduce the weight at any instance, there is a need for extensive computation, making the manual implementation of the BPNN aspect of the method computationally challenging. Thus, a future research direction could be the development of computer codes for each iteration computation.
3) The CRITIC method gives a higher weight for parameters and is less effective for the proposed CRITIC-BPNN method. A comparison of the CRITIC method and the fuzzy method in the previous work shows that the fuzzy method, which gives lower values of weight, is superior.
4) Based on the predicted output target to be zero, our initial error (error loss) obtained a value of -0.28, which signifies an accuracy of 28% above the target value. Subsequently, we commenced iterations, which reduced from -0.28 to -0.26 at the first iteration. It was further reduced to -0.248 at the second iteration. Further iterations produced reduced error loss values to the tune of -0.1 at the 23rd iteration, an improvement in accuracy by 64%, bringing up the accuracy value to roughly 10% above the target value.

Notations

δ_j	CRITIC standard deviation
r_{jk}	Measure of conflict
C_j	Quantity of information
W_j	CRITIC weight
Y_j	Activation function
a_j	Aggregate weight
O_i	Ouput i^{th} term
t_j	Correct target output for unit j
δ_j	Error measure for unit j
k	The number of output units
ΔW_{ji}	Change in weight
ΔW_2	Change in weight of parameter F
$W_{2(\text{new})}$	New weight of parameter F
ΔW_1	Change in weight of parameter D
$W_{2(new)}$	New weight of parameter D
ΔV_{01}	Change in weight of parameter A
$V_{01(new)}$	New weight of parameter A
ΔV_{11}	Change in weight of parameter C
$V_{11(new)}$	New weight of parameter C
ΔV_{02}	Change in weight of parameter B
$V_{02(new)}$	New weight of parameter B
ΔV_{12}	Change in weight of parameter E
$V_{12(new)}$	New weight of parameter E
BPNN	Back Propagation Neural Network

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APPENDIX

Table 1A. Iteration results from weight computations

Iteration	1	2	3	4	5	6	7	8	9
Error	-0.2800	-0.2600	-0.2489	-0.2335	-0.2197	-0.2074	-0.1962	-0.1861	-0.1770
W_1	0.2333	0.2185	0.2052	0.1934	0.1826	0.1730	0.1642	0.1562	0.1489
W_2	0.2333	0.2185	0.2052	0.1934	0.1826	0.1730	0.1642	0.1562	0.1489
V_{01}	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
V_{11}	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
V_{02}	0.1232	0.1217	0.1205	0.1194	0.1185	0.1178	0.1171	0.1165	0.1161
V_{12}	0.1232	0.1217	0.1205	0.1194	0.1185	0.1178	0.1171	0.1165	0.1161

Iteration	10	11	12	13	14	15	16	17	18
Error	-0.1687	-0.1610	-0.1540	-0.1475	-0.1415	-0.1359	-0.1308	-0.1260	-0.1216
W_1	0.1422	0.1360	0.1304	0.1251	0.1202	0.1157	0.1115	0.1076	0.1039
W_2	0.1422	0.1360	0.1304	0.1251	0.1202	0.1157	0.1115	0.1076	0.1039
V_{01}	0.1250	0.1250	0.125	0.125	0.1250	0.1250	0.1250	0.1250	0.1250
V_{11}	0.1250	0.1250	0.125	0.125	0.1250	0.1250	0.1250	0.1250	0.1250
V_{02}	0.1156	0.1152	0.1149	0.1146	0.1143	0.1141	0.1139	0.1137	0.1135
V_{12}	0.1156	0.1152	0.1149	0.1146	0.1143	0.1141	0.1139	0.1137	0.1135

Iteration	19	20	21	22	23
Error	-0.1174	-0.1174	-0.1135	-0.1100	-0.106
W_1	0.10049	0.1005	0.0973	0.0942	0.0914
W_2	0.10049	0.1005	0.0973	0.0942	0.0914
V_{01}	0.125	0.1250	0.1250	0.1250	0.1250
V_{11}	0.125	0.1250	0.1250	0.1250	0.1250
V_{02}	0.11338	0.1134	0.1132	0.1131	0.1130
V_{12}	0.11338	0.1134	0.1132	0.1131	0.1130

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