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PERFORMANCE EVALUATION AND PREDICTION OF MANUFACTURING ORGANIZAIONS UNDER SUSTAINABLE PERSPECTIVE

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ABSTRACT

The importance of this work exists in its ability to provide a data-driven and objective approach to rank sustainable manufacturing organizations through a comprehensive and holistic evaluation, considering various sustainability indicators.The study involves three stages namely: (1) Generation of alternatives using Box-Behnken design type, (2) Performance determination of alternatives through integrated DEA-GRA (3) Predicting the performance of the Alternatives through regression, Neural network and Deep Learning Neural network analysis. The adoption of the proposed comprehensive approach not only enhances the credibility and reliability of the rankings but also serves as a benchmark for other industries aiming to assess sustainability performance.

1. INTRODUCTION

Performance assessment is a crucial component in decision-making, especially when multiple alternatives are presented. The challenge is accentuated when these alternatives encompass numerous criteria, each with its own level of importance. Over the years, various methodologies have been proposed to tackle multi-criteria decision-making problems. Among these, Data Envelopment Analysis (DEA) and Grey Relational Analysis (GRA) have emerged as powerful tools. While DEA exhibits in estimating the capability of decision-making units which are havingplural inputs and outputs, GRA is adept at discerning relationships in complicated, indeterminate, and incomplete information systems. The integration of DEA and GRA – often termed as DEA-GRA – promises a robust approach that amalgamates the strengths of both methods. This paper delves into the intricacies of the integrated DEA-GRA method, exploring its potential to effectively determine the performance of alternatives, thereby offering decision-makers a comprehensive tool for informed choices.

In developing possible alternatives, Design of Experiments (DOE) helps to shape for any system to extract the maximum amount of information using a minimum number of experiments on it. The actual "designs" within DOE are systematic arrangements of conditions under which observations are made.Without these structured designs, experimental research or numerical simulation could be haphazard, inefficient, and less conclusive.

In performance evaluation and ranking, Predictions act as a compass, pointing decision-makers in the direction of favorable outcomes while helping them steer clear of potential pitfalls. As predictive tools and methodologies, like regression analysis, neural network prediction and deep learning techniques may be adopted.

While regression offers a simple and interpretable way to predict outcomes based on input variables, neural networks and deep learning provide tools for tackling more complex and non-linear relationships, especially in large, unstructured datasets. The choice between these methods should be driven by the nature of the data, the complexity of the problem, and the computational resources available.

2. LITERATURE REVIEW

Mohammad SadeghPakkar (2016) [1] developed an integrated AHP-DEA-GRA method which is implemented in case of selection of suitable site for dumping nuclear waste.

Frank Medel-Gonzáleza et al., (2016) [2]measured the sustainability performance measurement by using the Balanced Scorecard and Analytic Network Process in Cuban organizations and Ruth Banomyong et .al(2017) [3] designed the measurement of sustainable supply chain performance which has 14 indicators each with three dimensions.

Muhammad Waris et al., (2019) [4] evolved AHP model for the measurement of sustainable procurement index values in case of construction sector in Malasia

Ioannis E. Tsolas (2019) [5] developed integrated GRA-DEA approach for the ranking of the exchange traded funds (ETFs) in a best manner and proved that their procedure is better than DEA method.

Chun-Ho Chen (2019) [6] developed an integrated GRA-TOPSIS method for addressing the problems relating to supplier selection.

In respect of prediction, MemLang.J., (2008) [7] analyzed categorical data through logistic regression and presented the advantages over ANOVA. Hussein Alkharusi (2012) established the relationship between methods that are useful in teaching andin evaluation of standardized mathematics test through coding methods. ÇiğdemArıcıgilÇilan and Mustafa Can (2014) [8] applied Categorical Regression Analysis (CATREG) to study the influence of some factors which are crucial in the evaluation of Students pursuing MBA and their efficiency at Institution of Business Economics of Istanbul University. Venkataramana, M., M. Subbarayudu, M. Rajani, K.N. Sreenivasulu (2016) [9] developed a procedure how to applycategorical independent variables in a regression model which is used for coding methods. Antônioet al. (2020) [10]applied logistic regression, to address with dichotomous types of dependent variables.

Ahmed et al (2022) [11] presented application of ANNs in construction industry under sustainable perspective. The authors opined that application of ANNs in the field of industrial engineering is promising.

Ranjitsinh and Rahul (2019) [12], developedprediction model based with ANNfor evaluation offoundry industry performance. The authors opined that the proposed model is useful for improving industry performance under sustainable perspective.

Agrawal, et al (2023) [13] explored the applications of AI in Sustainable manufacturing during 2010-2021 through literature review. The author put forward that these applications will be useful to the researchers and industry practitioners

Aparna and jianyu (2023) [14] addressed sustainability in decision support in agile manufacturing. The authors developed methods which are data-driven in Artificial intelligenceby using machine learning in decision support in manufacturing.

3.METHODOLOGY

The proposed methodology is presented blow

Step 1: Problem Definition and Objective Setting

In this study, performance analysis and predicting the performance of sustainable manufacturing organizations is considered as an objective.

Step 2: Identify the key factors

In this study, the key factors are considered from the literature (Boddu Raju and V. V. S. Kesava Rao, 2021) for performance evaluation and ranking of sustainable manufacturing organizations.

Step 3: Generation of Empirical data

Possible Alternatives are generated through Box-Behnken design type of design of experiments using 21 factors at three levels.

Step4: Perform the evaluation based on the designed matrix

In this study, Performance evaluation of generated alternatives of sustainable manufacturing organization is done using integrated DEA and GRA. The detailed procedure is given in the following steps.

Step 4.1: Normalize the decision matrix.

Normalization formulae are presented below.

$$x_{kj} = \frac{x_{kj} - \min x_k(j)}{\max x_k(j) - \min x_k(j)} \text{......For benefit attribute}$$

$$x_{kj} = \frac{\max x_k(j) - x_{kj}}{\max x_k(j) - \min x_k(j)} \text{......For cost attribute}$$

x_{kj}=normalized value of k^{th} attribute of j^{th} alternative

Step 4.2 Determine absolute differences

The absolute difference are derived by the following the equation

$x_{kj} = |x_{0j} - x_{kj}|$

Step 4.3 Selection of maximum and minimum absolute differences

The Δmin and Δmax are evolved from the compared series and the referential series as per the equation state below

$\Delta\min = \min(x_{kj})$; $\Delta\max = \max(x_{kj})$;

Step 4.4 Determine grey relation coefficient

The above mentioned coefficient is obtained by the relation shown below

$$\xi_{kj} = \frac{\Delta\min + \rho\Delta\max}{\Delta_{kj} + \rho\Delta\max}$$

ρ : the distinguishing coefficient ρ is fixed as0.5

Step 4.5 Determine optimistic grey relation grade

Optimistic grey relation grade is obtained by solving the dual model (Pakkar, 2016) as discussed below.The model is solved through Lingo 8.0 by developing Code to the model

$$\Gamma_k = \max \sum_{j=1}^{n} w_j \xi_{kj} - w_0$$

$$\text{s.t.} \sum_{j=1}^{n} w_j \xi_{ij} - w_0 \leq 1 \ \forall i,$$

$$w_j \geq e_j \forall_j$$

w_0 free.

Step 4.6 Determine Pessimistic grey relation grade

Pessimistic grey relation grade is obtained by solving the dual model (Pakkar, 2016) as discussed below.The model is solved by through Lingo 8.0 by developing Code to the model.

$$\Gamma'_k = \max \sum_{j=1}^{n} w'_j \xi_{kj} + w'_0$$

$$\text{s.t.} \sum_{j=1}^{n} w'_j \xi_{ij} - w'_0 \geq 1 \, \forall i,$$

$$w'_j \geq e_j \forall_j$$

w_0 free.

Γ'_k =grey relation grade from pessimistic pessimistic perspective;

Step 4.7 Determine normalized compromised grey relation grade

Normalized grey relation grade is obtained from the following relation as discussed by (Zhou et al., 2007).

$$\Delta_k(\beta) = \beta \frac{\Gamma_k - \Gamma_{min}}{\Gamma_{max} - \Gamma_{min}} + (1-\beta) \frac{\Gamma'_k - \Gamma'_{min}}{\Gamma'_{max} - \Gamma'_{min}} \quad \textbf{(9)}$$

$\Gamma max = max(\Gamma k)$; $\Gamma min = min(\Gamma k)$; $\Gamma' max = max(\Gamma' k)$; $\Gamma' min = min(\Gamma' k)$; $0 \leq \beta \leq 1$ $\Delta k(\beta)$ is a normalized compromise grade And it s value lies in the range [0,1].

Step 4.8 Determine Grading of alternatives

The alternatives are then graded in decreasing order using normalized compromised gray relation grade.

Step5: Predicting the performance through Regression analysis

In this study, regression analysis is employed to decode the intricate relationships between sustainability indicators and the performance metrics of manufacturing organizations.regression analysis is employed with 21 sustainability indicators as independent variables and normalized grey relation grade as dependent variable.

Step6: Predicting the performance through Neural Network Analysis

This study embarks on an exploration of applying neural network analysis to estimate the performance trajectories of manufacturing organizations in light of their sustainability initiatives. Neural network tool box of Matlab is used for implementation of Neural Network Analysis.

Step7: Predicting the performance through Deep Learning Neural Network Analysis

A deep neural network has more than one hidden layer. Each layer extracts features of the input data.Training a DNN involves feeding it data and adjusting the weights of the network to optimize the predictions for normalized grey relation grade of the alternatives generated through design of experiments.

5.0 ILLUSTRATION OF THE PROPOSED METHODOLOGY

5.1 Key factors of performance of manufacturing organizations under sustainable perspective.

In this work, 21 variables under five sectors are taken for computation and grading of alternatives manufacturing organizations under sustainable perspective. The variables under the five criteria are presented in table 1 as shown below.

Table 1: Criteria and their attributes

Criteria	Attribute	Description
Sustainable Manufacturing (SM)	SM1	Energy Consumption per Unit of Production(kWh)
	SM2	Greenhouse Gas Emissions per Unit of Production (kgs of CO2)
	SM3	Water Usage per Unit of Production (Lts)
	SM4	Materials Efficiency and Waste Reduction(%)
	SM5	Resources efficiency(%)
Supply Chain Management (SCM)	SCM1	supplier's carbon footprint (MT of CO2/year)
	SCM2	Carbon Emissions per Shipment (Kgs/shipment)
	SCM3	Supplier Collaboration on Sustainability on a 1 to 5 scale
	SCM4	Packaging Sustainability (use of non-recyclable materials-1; partially recyclable-3; eco-friendly materials-5)
Social Responsibility (SR)	SR1	Training and Development Investments (%)

	SR2	Community Investment and Contributions
	SR3	Employee satisfaction and engagement (%)
	SR4	Implementation of Health and Safety Performance protocols on a 1 to 5 numerical scale
Environmental Management (EM)	EM1	Pollution Prevention investment
	EM2	Carbon Footprint Reduction (%)
	EM3	Environmental Audits and Compliance (limited, Moderate and strong)
	EM4	Stakeholders satisfaction on a 1 to 5 likert scale
Organizational Performance (ORP)	ORP1	Social Impact Reporting (1 to 5 likert scale)
	ORP2	Employee satisfaction and retention (%)
	ORP3	Asset utilization
	ORP4	Cost savings from sustainability initiatives (%)

5.2 Generation of Alternatives

Alternative manufacturing organizations are generated through Box-Behnken design type. The details of the design type and levels of the factors are presented below.

Table 2. Details of the design

Study Type Response Surface **Subtype** Randomized

Design Type	Box-Behnken	**Runs**	348.00
Design Model	Quadratic	**Blocks**	No Blocks
Build Time (ms)	19.00		

Table 3: Levels of the Factors

Factor	Levels			Factor	Levels			Factor	Levels		
	L	M	H		L	M	H		L	M	H
SM1	10	25	50	SCM 3	1	3	5	EM2	10	25	50
SM2	5	25	50	SCM 4	1	3	5	EM3	1	3	5
SM3	10	50	100	SR1	1	3	5	EM4	1	3	5
SM4	10	25	50	SR2	1	3	5	ORP1	1000	5000	10000
SM5	25	50	75	SR3	25	50	75	ORP2	10	25	50
SCM 1	100	250	500	SR4	1	3	5	ORP3	25	50	75
SCM 2	5	25	50	EM1	1	3	5	ORP4	5	10	25

Table 4: Descriptive Statistics of the Factors

Factor	Total Count	Mean	StDev	Minimum	Maximum
SM1	348	30	9.603	10	50
SM2	348	27.5	10.803	5	50
SM3	348	55	21.61	10	100
SM4	348	30	9.603	10	50
SM5	348	50	12.004	25	75
SCM1	348	300	96.03	100	500

SCM2	348	27.5	10.803	5	50
SCM3	348	3	0.9603	1	5
SCM4	348	3	0.9603	1	5
SR1	348	3	0.9603	1	5
SR2	348	3	0.9603	1	5
SR3	348	50	12.004	25	75
SR4	348	3	0.9603	1	5
EM1	348	3	0.9603	1	5
EM2	348	30	9.603	10	50
EM3	348	3	0.9603	1	5
EM4	348	3	0.9603	1	5
ORP1	348	3	0.9603	1	5
ORP2	348	30	9.603	10	50
ORP3	348	50	12.004	25	75
ORP4	348	15	4.802	5	25

5.3 Performance Evaluation of Alternatives

In this study, integrated GRA-DEA Method is implemented for calculation and grading of attentive manufacturing organizations depended on sustainable perspective.The normalized grey relation grades represent the responses of the alternatives.Optimistic, Pessimistic and Normalized performance grades of 348 experiments (alternatives) are determined and presented in the following figure 1

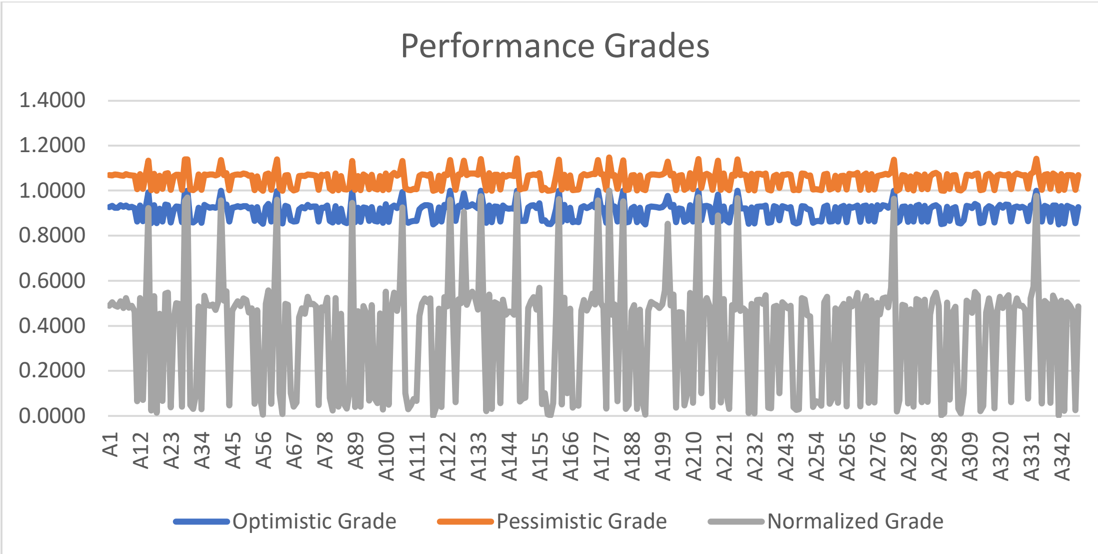

Figure 1: Performance of Grades of Alternatives

5.4 Regression Analysis

A comprehensive dataset is generated for 348 empirical sustainable manufacturing organizations with 21 attributes or sustainable practices under five major constructs
In this study, sustainable performance of business organizations is considered as dependent variable are and the proposed 21 attributes are considered as independent variables. These predictive equations were made for linear regression models. The predictive equation of sustainable performance of organizations in terms of normalized Grade is presented below.

5.4.1. Regression Equation: Regression equation so obtained is presented below.

Normalized Grade = -3.2633 + 0.004934*SM1 + 0.004741*SM2 + 0.002677*SM3 + 0.006135 *SM4 + 0.004324* SM5 + 0.000661* SCM1 + 0.0053458 SCM2 + 0.06276*SCM3+ 0.05668*SCM4 + 0.05675*SR1 + 0.04734*SR2 + 0.004603*SR3 + 0.05329* SR4+ 0.05010*EM1 + 0.005522*EM2 + 0.06721*EM3 + 0.06209*EM4 + 0.05300*ORP1+ 0.004779*ORP2 + 0.004333*ORP3 + 0.012169*ORP4

5.4.2 Analysis of Variance: Especially in cases of ANOVA designs with more than one independent variable, it helps in understanding how close the model suits to the data and which factors or interactions between factors significantly predict the dependent variable. The outcome of above analysis is shown in the table below

Table 5. Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	21	21.7598	1.03618	349.18	0.000

SM1	1	0.7791	0.7791	262.55	0.000
SM2	1	0.9103	0.91025	306.74	0.000
SM3	1	1.1612	1.16119	391.3	0.000
SM4	1	1.2043	1.20425	405.82	0.000
SM5	1	0.935	0.93504	315.1	0.000
SCM1	1	1.3974	1.39742	470.91	0.000
SCM2	1	1.1569	1.15686	389.84	0.000
SCM3	1	1.2605	1.2605	424.77	0.000
SCM4	1	1.0279	1.02791	346.39	0.000
SR1	1	1.0305	1.0305	347.26	0.000
SR2	1	0.7171	0.71707	241.64	0.000
SR3	1	1.0595	1.05953	357.04	0.000
SR4	1	0.9089	0.90888	306.28	0.000
EM1	1	0.8032	0.80321	270.67	0.000
EM2	1	0.9759	0.97591	328.87	0.000
EM3	1	1.4454	1.44535	487.06	0.000
EM4	1	1.2337	1.23365	415.72	0.000
ORP1	1	0.8988	0.89881	302.89	0.000
ORP2	1	0.7308	0.73084	246.28	0.000
ORP3	1	0.9388	0.93877	316.35	0.000
ORP4	1	1.1847	1.18471	399.23	0.000

The p-value as derived from the regressmodel proved very satisfactory and is significant at an a-level of 0.05. This above result indicates that at least one coefficient is different from zero. It is also observed that all the attributes are significant in determination of sustainable performance of organizations.

5.4.3 Model Summary: Regression model summary is shown in the following table

Table 6: Model Summary

S	R-sq	R-sq(adj)	R-sq(Pred)
0.0545	95.74%	95.47%	95.67%

The R^2 value and Adjusted R^2value are both 95.74% which proves that the regression models design is very good.

5.4.4 Mean squared Error: The mean squared error obtained in the study is 0.0027 which shows that the fitted model is good.

5.4.5 RMSE: A smaller RMSE of 0.0527 is obtained in the study indicates that model is best fitted.

5.4.6 Predicted Performance:Regression equation obtained in the study is used to predict the normalized performance grade of given alternates with the given inputs and the predicted results are presented below.

Table 7: Predicted Responses of the Given Input data (Regression Analysis)

Alts	SM1	SM2	SM3	SM4	SM5	SCM1	SCM2	SCM3	SCM4	SR1	SR2	SR3	SR4	EM1	EM2	EM3	EM4	ORP1	ORP2	ORP3	ORP4	Normalized grade	Rank
VA1	20	31	42	25	55	307	35	2	3	3	3	36	3	3	28	3	3	2	19	50	11	0.0495	7
VA2	21	21	34	18	38	304	18	3	3	3	3	52	3	2	15	4	2	1	47	54	12	-0.0938	10
VA3	23	19	75	15	36	254	46	2	2	3	3	66	2	2	24	2	2	3	27	68	11	-0.0281	8
VA4	30	27	52	19	49	183	24	5	2	3	3	48	3	3	20	3	3	2	33	41	15	0.1224	5
VA5	19	29	39	12	42	446	31	3	2	4	3	48	1	4	29	4	2	4	26	39	21	0.2472	3
VA6	21	28	50	12	51	350	28	4	2	2	2	39	3	3	28	3	2	4	29	43	22	0.1294	4
VA7	20	30	59	22	49	155	22	5	4	3	3	70	3	4	39	4	3	3	22	71	10	0.6017	1
VA8	16	30	56	16	45	130	21	4	2	4	3	39	3	3	17	4	4	2	19	38	10	-0.0840	9
VA9	25	19	67	26	46	259	43	4	4	2	2	34	4	3	26	4	3	4	30	62	11	0.4514	2
VA10	38	31	58	24	45	282	12	1	3	3	3	47	2	3	31	3	2	5	44	39	10	0.1000	6

5.5 Neural Network Analysis

Linear models might fall short in capturing the convoluted interactions of these variables, but ANNs thrive in this complexity. Their ability to 'learn' from data means that they can continually refine their predictions, offering insights that are both deep and actionable.

In the study, three layered network is chosen with the input (i), a hidden layer and the output layer with single node. Input layer contains 21 nodes (Sustainable factors) and output layer consistsone node (Normalized performance grade) are considered. For the training and testing data on 348 runs of DoEs (alternatives) are considered with back-propagation module in the MATLAB is used. The results of the Neural Network Analysis are presented below.

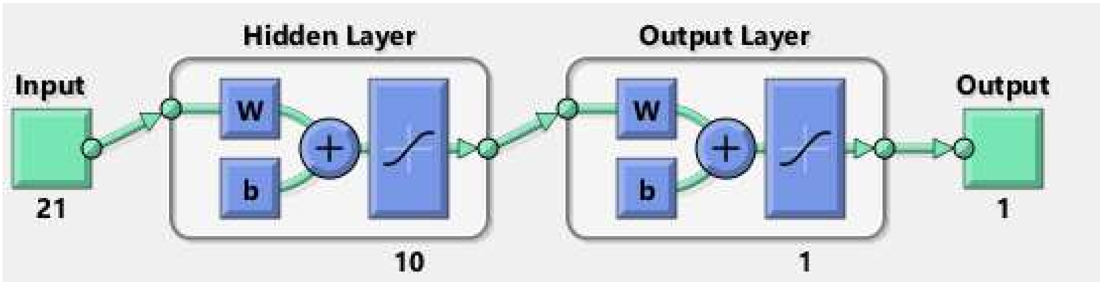

Figure 1: Neural network Architecture

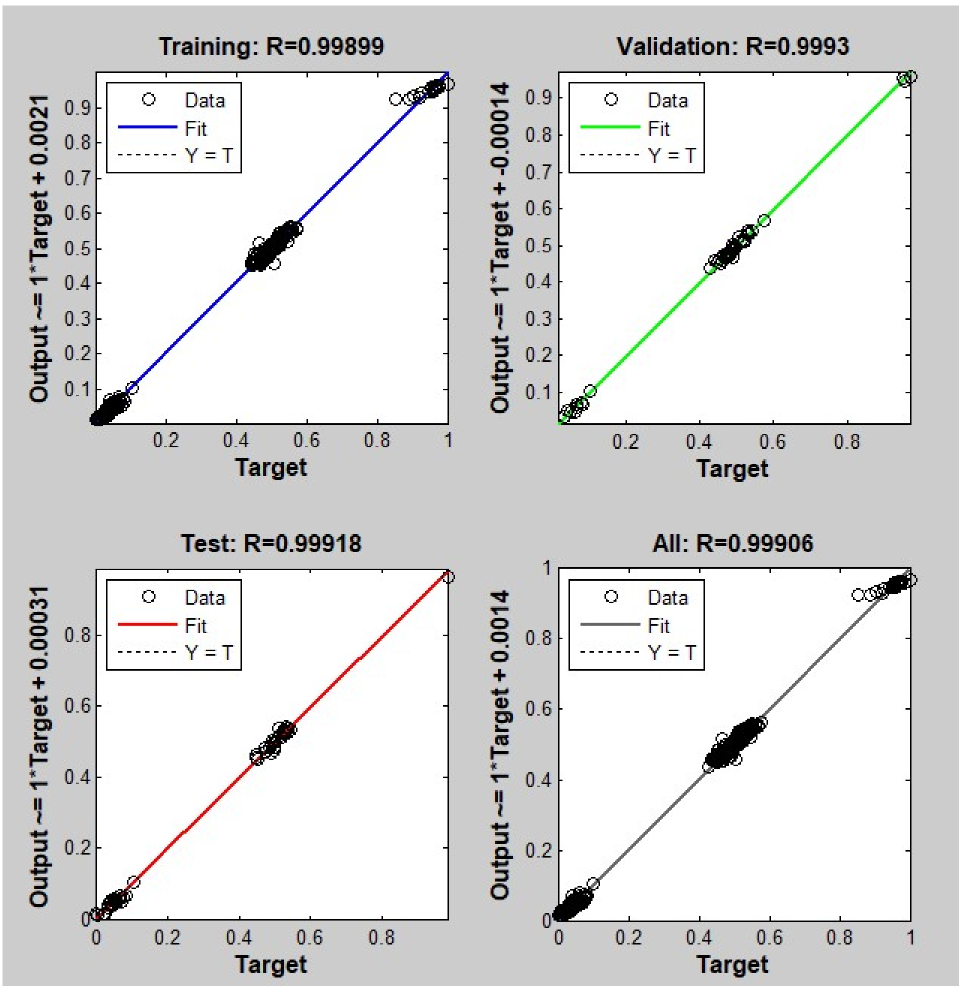

Figure2:Regression Coefficients

As shown in Figure 2, the regression coefficient of the network during training, testing and validation were 0.99899, 0.9993, and 0.99918 respectively which indicates the good prediction.

5.5.1Mean squared Error: In the neural network analysis, the mean squared error obtained in the study is 0.00012 which is very smaller. Which indicates superior performance by neural net work.

5.5.2 RMSE: A smaller RMSE of 0.0113 is obtained in the neural network analysis study indicates that signifies that the model's predictions have smaller errors when compared with actual values

5.5.3 Prediction

The trained neural network is used to predict the normalized performance grade of given alternates with the given inputs and the predicted results are presented below.

Predicted Responses of the Given Input data

Table 8: Predicted Normalized Performance Grade and the Ranking

Alts	SM1	SM2	SM3	SM4	SM5	SCM1	SCM2	SCM3	SCM4	SR1	SR2	SR3	SR4	EM1	EM2	EM3	EM4	ORP1	ORP2	ORP3	ORP4	Normalized grade	Rank
VA1	20	31	42	25	55	307	35	2	3	3	3	36	3	3	28	3	3	2	19	50	11	0.0526	7
VA2	21	21	34	18	38	304	18	3	3	3	3	52	3	2	15	4	2	1	47	54	12	0.0536	6
VA3	23	19	75	15	36	254	46	2	2	3	3	66	2	2	24	2	2	3	27	68	11	0.0405	9
VA4	30	27	52	19	49	183	24	5	2	3	3	48	3	3	20	3	3	2	33	41	15	0.0412	8
VA5	19	29	39	12	42	446	31	3	2	4	3	48	1	4	29	4	2	4	26	39	21	0.0774	3
VA6	21	28	50	12	51	350	28	4	2	2	2	39	3	3	28	3	2	4	29	43	22	0.0553	5
VA7	20	30	59	22	49	155	22	5	4	3	3	70	3	4	39	4	3	3	22	71	10	0.8885	1
VA8	16	30	56	16	45	130	21	4	2	4	3	39	3	3	17	4	4	2	19	38	10	0.0659	4
VA9	25	19	67	26	46	259	43	4	4	2	2	34	4	3	26	4	3	4	30	62	11	0.2729	2
VA10	38	31	58	24	45	282	12	1	3	3	3	47	2	3	31	3	2	5	44	39	10	0.0121	10

6.0. RESULTS AND DISCUSSION

6.1 Comparison of rankings: Comparisons of ranking prediction of the 10 empirical alternatives are done and presented in the table 9.

Table 9: Comparison of Rankings Prediction

Alts	Rank by RA	Rank By ANN
VA1	7	7
VA2	10	6
VA3	8	9
VA4	5	8
VA5	3	3
VA6	4	5
VA7	1	1
VA8	9	4
VA9	2	2
VA10	6	10

For both methodologies, there was remarkable consistency in the predicted rankings of alternatives VA7, VA9, VA5 that sat at the top performers having ranks of 1,2 and 3 respectively. This consistency suggests that both methods effectively identify the primary drivers impacting performance. It's reassuring to see that traditional regression, with its long-standing foundation, holds its ground even against the computational prowess of neural networks in identifying major influencers. Pearson correlation of Rank by RA and Rank By ANN = 0.588 with p-Value = 0.074 indicates that the correlation is significant 7.5% level.

A key difference between the two methodologies lies in their interpretability. Regression analysis, with its transparent mathematical framework, offers clear insights into how each independent variable affects the dependent variable. This makes it invaluable for scenarios where understanding the relationship between variables is crucial. In contrast, neural networks, often termed as "black boxes," provide less direct interpretability, making it harder to deduce exactly why a particular prediction was made. However, this complexity grants neural networks their adaptability and flexibility in handling intricate datasets.

7. CONCLUSIONS

The combined DEA-GRA approach offered a comprehensive evaluation framework. While DEA pinpointed efficiency scores, GRA provided a more relative ranking based on the organization's alignment with sustainable best practices. The duality of this method ensures that while operational efficiency is rewarded, there's an emphasis on sustainable practices. This is crucial in a world where operational efficiency alone isn't enough; alignment with global sustainability goals is paramount.

The combined approach of performance evaluation by DEA-GRA and predictive modeling using regression analysis and ANN offers manufacturing organizations a comprehensive toolkit to navigate the challenges of sustainability. While each method has its strengths and limitations, their collective insights pave the way for a more sustainable future in manufacturing.

Future Scope:The DEA-GRA approach, having shown its efficacy, can be extended to a wider range of industries beyond the manufacturing sector. Sectors like agriculture, energy, and logistics could benefit from a combined efficiency and sustainability analysis.

As computational capabilities improve, deep learning architectures, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), can be explored to model more complex relationships and patterns in manufacturing sustainability.

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