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Research Article

Generalized Regression Neural Network (GRNN) for the Prediction of CRDI Engine Responses Fuelled with Pongamia Biodiesel

Nithyananda BS[1], GV Naveen Prakash[2], VN Manjunath Aradhya[3], Basavaraju HT[4], DS Guru[5], Anand A[6]

[1]Assistant Professor, [2]Professor, Department of Mechanical Engineering, Vidyavardhaka College of Engineering, Mysuru, Karnataka, India.
[3,4]Department of Computer Applications, JSS Science and Technology University, Mysuru, Karnataka, India.
[5]Department of Studies in Computer Science, University of Mysore, Mysuru, Karnataka, India.
[6]Assistant Professor, Department of Mechanical Engineering, National Institute of Engineering, Mysuru, Karnataka, India.
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I N F O

Corresponding Author:
Nithyananda BS, Department of Mechanical Engineering, Vidyavardhaka College of Engineering, Mysuru, Karnataka, India.
E-mail Id:
bsn@vvce.ac.in
Orcid Id:
https://orcid.org/0000-0002-7736-3729
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A B S T R A C T

The application of General Regression Neural Network (GRNN) for the prediction of performance and emission responses of Common Rail Direct Injection (CRDI) engine using B5, B10 and B20 blend of pongamia biodiesel is presented in this paper. Data required for the prediction is obtained through experimentation on CRDI engine by varying parameters like injection pressure, injection timing and fuel preheating temperature. The experiments were conducted based on L9 Taguchi Orthogonal Array (OA). The experimental values for performance parameters like brake thermal efficiency, specific fuel consumption and emission parameters like CO, Nox and HC were recorded and used for GRNN. GRNN model is trained with 70% of samples and is validated with testing dataset of 30% by selecting optimum spread parameter (σ). The proposed model was found to be reliable and provides a cost effective way for determining performance parameters of engine. The results presented in this study substantially promote the use of GRNN model for the prediction of parameters in CRDI engine.

Keywords: Neural Networks, General Regression Neural Network (GRNN), Orthogonal Array (OA), Pongamia Biodiesel, CRDI

Introduction

The availability of fossil fuels is decreasing day by day and there is an increase in demand for the fossil fuels.[1] This poses a major challenge to technology to look for alternative fuels which are environment friendly. Biodiesel is found to be the best alternative fuel to diesel, which can produced from plant oils and animal fats. Biodiesel is renewable, oxygen rich and biodegradable.[1] The use of edible plant oils kicks up a controversy leading to food versus fuel debate. Hence, the idea of using edible oils for biodiesel production in India is not encouraged. The focus was given on second generation feedstocks like non edible oils for biodiesel. Non edible oils like neem, pongamia, mahua, simarouba oil etc., are being investigated as fuel alternative to diesel.[2] These oils are of high viscosity and high density, hence they are not used directly in diesel engine.[3] Oils are transesterified to reduce viscosity using methanol and NaOH/ concentrated sulphuric acid as catalyst based on Free Fatty Acid (FFA) percentage.

Tesfa et al.,[4] have investigated biodiesel produced from waste oil, corn oil and rapeseed oil. The emission characteristics of CI engine are studied using B10, B20, B50 and B100 blend. They found that Nox emissions for biodiesel run engine increased by 20% and other emissions got reduced. The performance and emission study of diesel engine fuelled with castor and soybean biodiesel was investigated by Bueno et al.[5] They compared performance and emissions of biodiesel with diesel. The effect of compression ratio (CR) on performance and emissions of simarouba biodiesel run engine was investigated by Naveena et al.[6] They found that efficiency is better at CR of 16.5 with low emissions.

The neat biodiesel produced from different oil feedstocks are blended with diesel in different proportions. The biodiesel blends are used in CI engine to study performance, combustion and emission characteristics by varying different engine operating parameters. The economic and technical feasibility of using biodiesel as fuel in CI engines are investigated by various researchers. Many researchers suggested for extensive study on biodiesel and also recommended for implementing any prediction networks for responses prediction to reduce experimental cost and time.

In this research work, pongamia oil is identified and selected as potential biodiesel feedstock. The pongamia oil is taken through Transesterification process to produce biodiesel. The neat biodiesel obtained after transesterification process is blended with diesel by 5%, 10% and 20% volume. The prepared blends are characterized for their fuel properties and used in CRDI engine. The parameters like injection pressure, injection timing and fuel temperature are considered for investigation based on comprehensive review of literature. Each blend is tested on CRDI engine by varying parameters and responses are recorded. From the literature review it is found that only few authors have used GRNN for engine applications. Therefore an effort is made to implement General Regression Neural Network (GRNN) for the prediction of engine performance and emission responses.

General Regression Neural Network (GRNN)

GRNN is proposed by Specht which is special type of radial basis function networks.[7-9] GRNN is memory based network with a single pass of training using labelled data sets.[10] In GRNN, there is no concept of learning, initial weights, optimum hidden neurons etc., GRNN composed of four layers namely input layer, pattern/ hidden layer, summation layer and output layer.[11] The input layer stores the information of input data and the number of neurons in this layer is equal to input vector dimension. Then input neurons send the data to hidden layer neurons. The hidden neurons transform the data into nonlinear space. The hidden neurons memorize the relationship between input and target responses. The number of neurons in hidden layer is equal to number of training samples. The summation layer consists of numerator and denominator summation neurons. Numerator summation neuron multiplies the training data and activation function and summates it. Denominator neuron summates the activation function. This layer send both numerator and denominator part to the next layer. The output layer calculates the output by dividing numerator part by denominator part of summation layer. The main advantage of GRNN is that no iterative training is required as in the case of back propagation network.[7,12] The general architecture of GRNN is shown in Figure 1. The prediction of output in GRNN is estimated using Equation 1.[13,14]

$$\hat{y}(x) = \frac{\sum_{i=1}^{n}\left[y_i \exp\left(\frac{-D_i^2}{2\sigma^2}\right)\right]}{\sum_{i=1}^{n}\exp\left(\frac{-D_i^2}{2\sigma^2}\right)}$$

Where Predicted output

y_i = target output

D_i= Euclidean distance

n = number of training samples

σ = spread parameter

The Euclidean distance between new input and training sample input is estimated using Equation 2.[14]

$$D_i^2 = (X - X^i)^T (X - X^i)$$

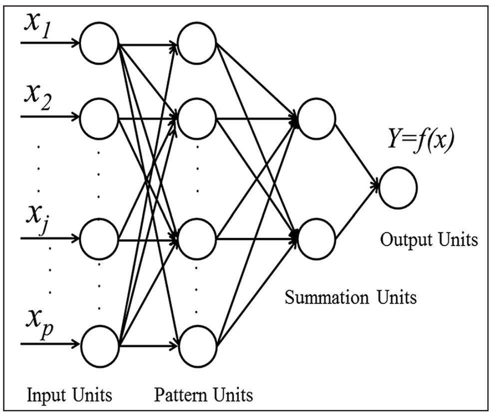

Figure 1.GRNN Architecture

Experimentation and Discussion

Design of Experiments (DoE) by Taguchi Method

DOE is a statistical technique employed to plan experiments in which factors of interest are varied over as definite range. The experimentation on engine proved to be time consuming and costly. Therefore DOE is implemented to reduce the number of experiments to a practical level without compromising on the accuracy of results. In this study, injection pressure, injection temperature and fuel temperature are considered for investigation for PB5, PB10 and PB20 biodiesel blend. Each parameter is varied at three levels as shown in Table 1. The full experiments considering 3 factors and 3 levels would lead to 27 experiments for each blend. This becomes difficult to conduct the experiments. Hence Taguchi technique is used which reduces the experiments to practical level by considering parameters that truly affects the output. The parameters which truly influence the output are considered as per L9 design array of Taguchi. For the same 3 factor and 3 level, the L9 Orthogonal Array (OA) can be used based on Taguchi which requires only 9 experiments. The factors levels are weighted equally since Taguchi array is orthogonal. The experiments are conducted as per Taguchi L9 design array for each blend and results are tabulated as shown in Table 2.

Experimentation on CRDI Engine

The experiments are conducted for PB5, PB10 and PB20 blend by varying injection pressure, injection timing and fuel temperature as per L9 Taguchi OA. The CRDI engine and five gas analyzer is used for experimentation. The performance parameters like BTE and BSFC are considered for analysis. Also, emission responses such as CO, HC and Nox are considered. The technical specifications of CRDI engine as shown in Table 3. The experimental results obtained are shown in Table 4.

Table 1.Levels of Control Parameters

Parameters	Levels		
	Level 1	Level 2	Level 3
Injection Pressure bar	400	500	600
Injection Timing ºCA before TDC	21	23	25
Fuel Temperature ºC	30	35	40

Table 2.Taguchi L9 Orthogonal Array

Trials	IP (A) bar	IT (B) º CA before TDC	FPT (C) º C
1	400	21	30
2	400	23	35
3	400	25	40
4	500	21	35
5	500	23	40
6	500	25	30
7	600	21	40
8	600	23	30
9	600	25	35

Table 3.Specifications of CRDI Engine

Product	CRDI VCR Research Engine Setup
Model	244
Cooling	Water cooled
Power	3.5kW
Compression ratio	12:1 to 18:1
Standard Injection Timing	23˚ b TDC
Standard Injection Pressure	16 bar
Bore	85.5 mm
Stroke	110 mm
Capacity	661 cc
Overall Dimensions	2000 x 2500 x 1500

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Table 4.Experimental Results for Pongamia Biodiesel

S. No.	Blend	Parameters			Responses				
		IP bar	IT º CA before TDC	FT º C	BTE %	BSFC Kg/ kw-h	CO %	HC PPM	No_x PPM
1	PB5	400	21	30	26.04	0.32	0.318	17	655
2		400	23	35	27.51	0.31	0.289	9	771
3		400	25	40	27.94	0.32	0.281	11	829
4		500	21	35	27.62	0.3	0.207	11	754
5		500	23	40	27.34	0.31	0.168	5	942
6		500	25	30	25.21	0.33	0.255	15	1093
7		600	21	40	27.6	0.3	0.139	6	967
8		600	23	30	24.02	0.35	0.255	9	988
9		600	25	35	26.34	0.32	0.139	6	1206
10	PB10	400	21	30	26.62	0.33	0.379	20	608
11		400	23	35	25.68	0.34	0.471	26	629
12		400	25	40	28.12	0.31	0.25	16	804
13		500	21	35	26.8	0.32	0.269	17	705
14		500	23	40	27.14	0.32	0.203	18	900
15		500	25	30	25.84	0.34	0.242	14	998
16		600	21	40	28.1	0.31	0.179	9	814
17		600	23	30	26	0.33	0.295	13	906
18		600	25	35	27.13	0.32	0.175	11	1129
19	PB20	400	21	30	28.12	0.31	0.336	29	712
20		400	23	35	28.33	0.31	0.329	29	837
21		400	25	40	26.87	0.32	0.298	27	993
22		500	21	35	27.09	0.32	0.274	25	872
23		500	23	40	28.48	0.31	0.256	24	996
24		500	25	30	27.05	0.32	0.265	21	1002
25		600	21	40	27.13	0.32	0.222	20	990
26		600	23	30	25.7	0.34	0.239	16	1127
27		600	25	35	27.08	0.32	0.28	16	1176

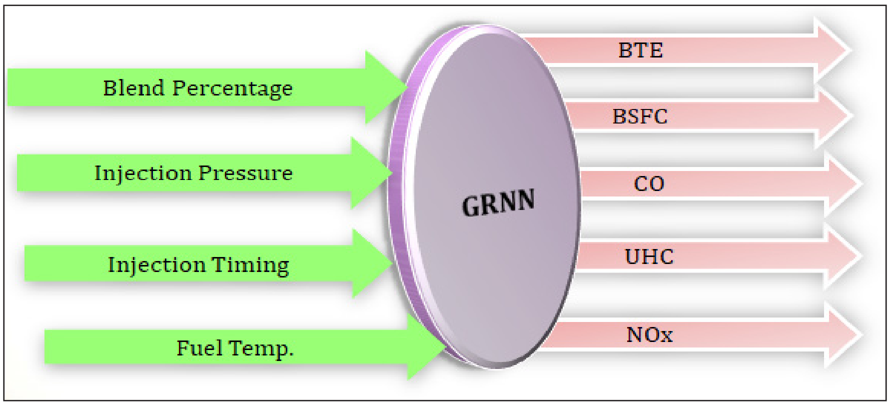

Figure 2.GRNN Model for Prediction

Table 5.Training Data of Pongamia Biodiesel

S. No.	Input Parameter				Output Parameter				
	Blend	IP	IT	FT	BTE	BSFC	CO %	HC	Nox
1	5	400	21	30	26.04	0.32	0.318	17	655
2	5	400	23	35	27.51	0.31	0.289	9	771
3	5	500	21	35	27.62	0.3	0.207	11	754
4	5	500	25	30	25.21	0.33	0.255	15	1093
5	5	600	23	30	24.02	0.35	0.255	9	988
6	5	600	25	35	26.34	0.32	0.139	6	1206
7	10	400	23	35	25.68	0.34	0.471	26	629
8	10	400	25	40	28.12	0.31	0.25	16	804
9	10	500	21	35	26.8	0.32	0.269	17	705
10	10	500	25	30	25.84	0.34	0.242	14	998
11	10	600	21	40	28.1	0.31	0.179	9	814
12	10	600	23	30	26	0.33	0.295	13	906
13	20	400	21	30	28.12	0.31	0.336	29	712
14	20	400	25	40	26.87	0.32	0.298	27	993
15	20	500	23	40	28.48	0.31	0.256	24	996
16	20	500	25	30	27.05	0.32	0.265	21	1002
17	20	600	21	40	27.13	0.32	0.222	20	990
18	20	600	25	35	27.08	0.32	0.28	16	1176

Table 7.Testing Data of Pongamia Biodiesel

S. No.	Input Parameter				Output Parameter				
	Blend	IP	IT	FT	BTE	BSFC	CO %	HC	Nox
1	5	400	25	40	27.94	0.32	0.281	11	829
2	5	500	23	40	27.34	0.31	0.168	5	942
3	5	600	21	40	27.6	0.3	0.139	6	967
4	10	400	21	30	26.62	0.33	0.379	20	608
5	10	500	23	40	27.14	0.32	0.203	18	900
6	10	600	25	35	27.13	0.32	0.175	11	1129
7	20	400	23	35	28.33	0.31	0.329	29	837
8	20	500	21	35	27.09	0.32	0.274	25	872
9	20	600	23	30	25.7	0.34	0.239	16	1127

GRNN Model Development

GRNN model establishes the relationship between input and output data based on probability density function.[15] Since experimentation on engine will leads to wastage of resources, time and proven to be costly. Hence prediction techniques like GRNN will benefit to predict the output for new input data. In the study, Gaussian radial basis function and linear function are used as activation function in the hidden layer and output layer respectively. The training of GRNN is very simple. The training of GRNN specifically directed towards finding an optimum spread parameter (σ), which is the only parameter to be determined.[16] The value of spread parameter affects the accuracy of prediction. There are no proper models to find optimum σ, trial and error approach is employed in this study to determine σ. Higher value of σ leads to exclusion of some of features in training datasets. Overfitting of model takes with smaller values of σ.[17]

In the study, 70% of total 27 experimental trials are dedicated for training and remaining 30% for testing and validation.

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The GRNN model is built using codes written on Matlab software. Above Figure 2, shows the input parameters and output parameters considered for developing the GRNN model. The spread parameter is varied 0.05 to 1 with step increments of 0.2. Thus 5 simulations were performed to obtain the optimum σ. The optimum σ is selected based on least error, obtained by comparing actual values and predicted values. The data used for training and testing the model is shown in above Table 5 and Table 6, respectively.

Result and Discussion

The prediction of engine performance and emission responses will be carried out. A total of 18 experimental datasets are used for training the model. The remaining 9 experimental datasets are used for testing and validation. The model built using 'newgrnn' function on Matlab software is simulated for different values of spread parameter. As a result of this, 5 simulations are performed. The best predicted output is selected based on minimum error. In this analysis, all the predicted values for responses are compared with the actual experimental values and absolute error is estimated as presented in Table 7. The predicted results of training datasets are comparable to their experimental values resulting in 100% prediction accuracy. Comparison of predicted results with actual experimental values for BTE, BSFC, CO, HC and NOx respectively is shown in Figures 3-7. From all the graphs we can conclude that the predicted values of different responses are closer to actual experimental values. Further, the predicted results for HC and Nox can be improved by considering more training datasets.

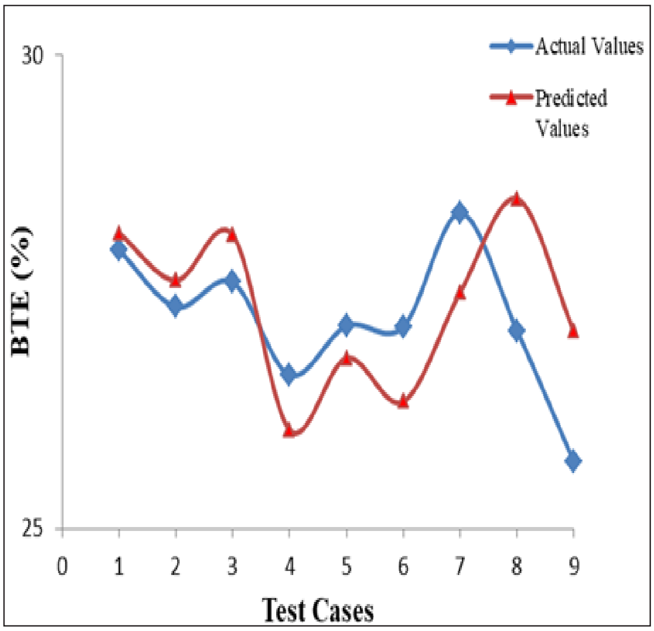

Figure 3.Comparison of Prediction Values with Actual Experimental Values for BTE

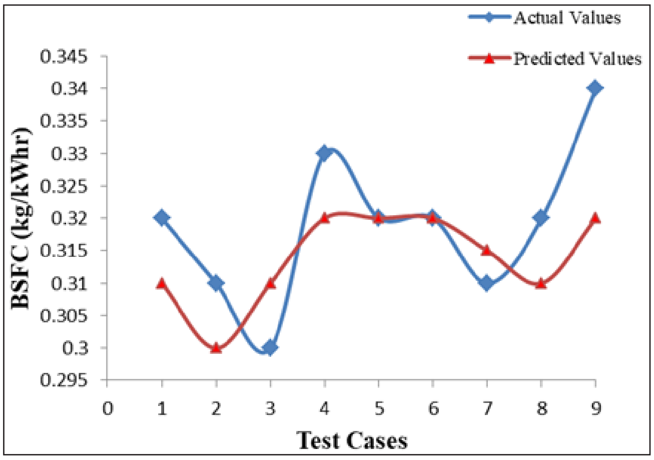

Figure 4.Comparison of Prediction Values with Actual Experimental Values for BSFC

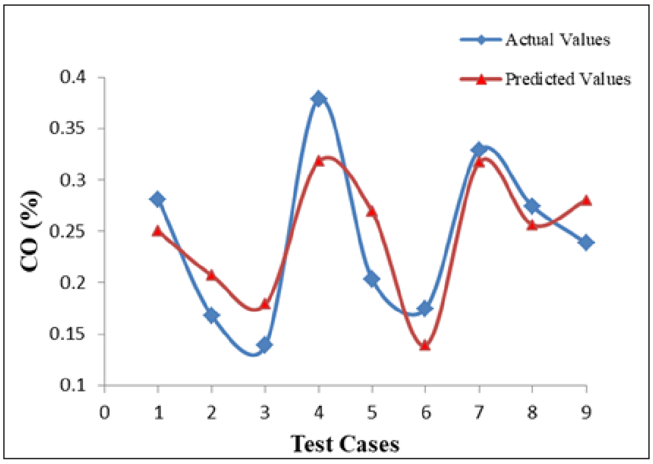

Figure 5.Comparison of Prediction Values with Actual Experimental Values for CO

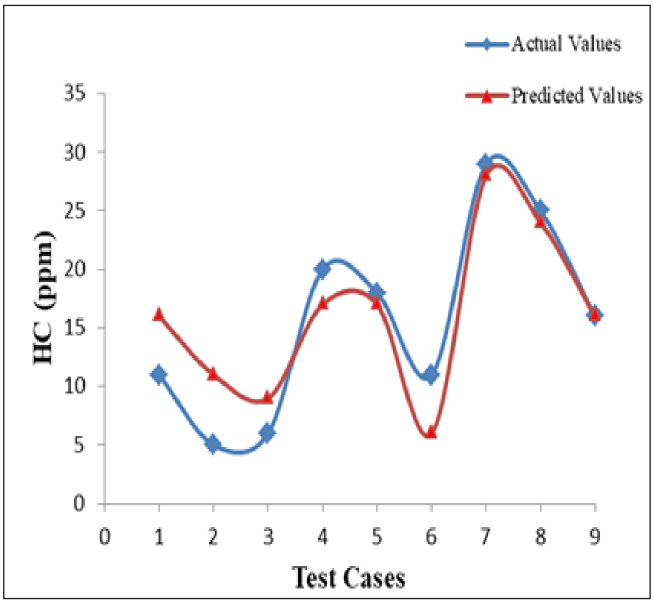

Figure 6.Comparison of Prediction Values with Actual Experimental Values for HC

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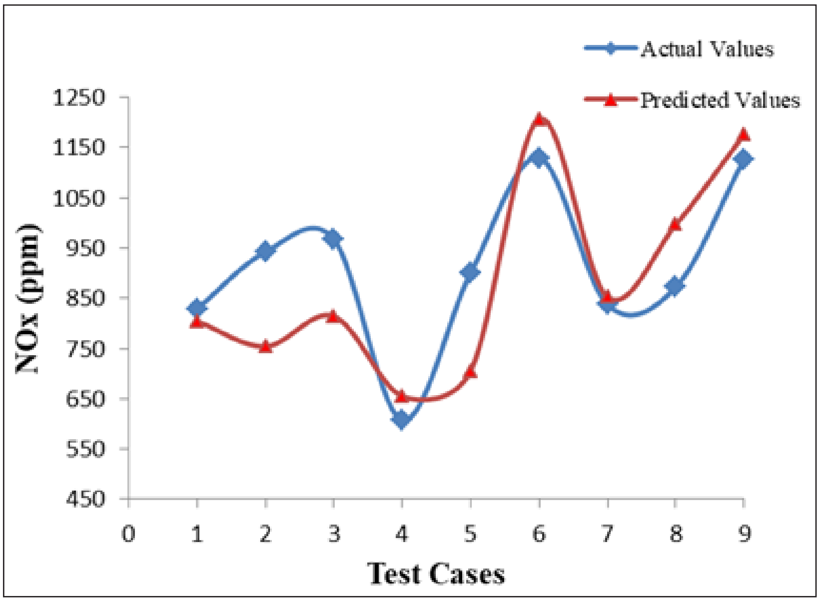

Figure 7.Comparison of Prediction Values with Actual Experimental Values for Nox

Table 8.Absolute Error for Different Responses of CRDI Engine

S. No.	Input Parameter				Absolute Error				
	Blend	IP	IT	FT	BTE (%)	BSFC (kg kWhr)	CO (%)	HC (ppm)	Nox (ppm)
1	5	400	25	40	0.18	0.01	0.031	5	25
2	5	500	23	40	0.28	0.01	0.039	6	188
3	5	600	21	40	0.5	0.01	0.04	3	153
4	10	400	21	30	0.58	0.01	0.061	3	47
5	10	500	23	40	0.34	0	0.066	1	195
6	10	600	25	35	0.79	0	0.036	5	77
7	20	400	23	35	0.835	0.005	0.012	1	15.5
8	20	500	21	35	1.39	0.01	0.018	1	124
9	20	600	23	30	1.38	0.02	0.041	0	49

Conclusion

General regression neural network is implemented to predict the performance and emission responses of CRDI engine. From the analysis, the optimum spread parameter for which prediction is more accurate was found to be 0.45. Prediction results of GRNN are in good agreement with actual experimental values for the performance responses such as BTE and BSFC as well as emission responses such as CO, HC and Nox. The experimental results indicated that the prediction accuracy of GRNN model is found to be acceptable. Therefore the GRNN model can be further explored for new datasets considering different engine parameters covering wide range.

References

1. Xue J, Tony EG, Alan CH. Effect of biodiesel on engine performances and emissions. *Renewable and Sustainable Energy Reviews* 2011; 15: 1098-1116.
2. Yahuza RI, Ejilah, Dandakouta H et al. Exhaust Emissions Characterization of a Single Cylinder Diesel Engine Fueled with Biodiesel-Ethanol-Diesel Blends. *Bioinformatics & Proteomics Open Access Journal,* 2017; 2(1).
3. Nair JN, Kaviti AK, Daram AK. Analysis of performance and emission on compression ignition engine fuelled with blends of Neem biodiesel. *Egyptian Journal of Petroleum* 2017; 26: 927-931.
4. Belachew T, Fengshou Gu, Mishra R et al. Emission Characteristics of a CI Engine Running with a Range of Biodiesel Feedstocks. *Energies* 2014; 7: 334-350.
5. Bueno AV, Pereira MPB, Pontes JVO et al. Performance and emissions characteristics of castor oil biodiesel fuel blends. *Applied Thermal Engineering* 2017; 559-566.
6. Naveena P, Vinod R, Prashanth Reddy. Experimental

Investigation on the Performance and Emission Characteristics of Simarouba Glauca Oil as an Alternate Fuel in Variable Compression Ignition Engine. *International Journal of Engineering Research & Technology* 2015; 4(6). ISSN: 2278-0181.

7. Yadav PK, Jaiswal KL, Singh K et al. A New ANN, GRNN and RBF Neural Network for Heart Disease Diagnosis. 2014; 3: 152-161.
8. Hojin L, Sungduk K, Kyewon J. The Study for Storm Surge Prediction Using Generalized Regression Neural Networks. *Journal of Coastal Research* 2018; 85: 781-785.
9. ChunHui Z, HongXiang T, Tao L. Analysis Based on Generalized Regression Neural Network to Oil Atomic Emission Spectrum Data of Type Diesel Engine. *Springer* 2011; 574-580.
10. Stegmayer G, Vega J, Gugliotta L et al. Estimation of the Particle Size Distribution of a Latex using a General Regression Neural Network. *International Federation for Information Processing* 2008; 276: 255-264.
11. Bendu H, Deepak BBVL, Murugan S. Application of GRNN for the prediction of performance and exhaust emissions in HCCI engine using ethanol. *Energy Conversion and Management* 2016; 122: 165-173.
12. Ozgur K. Generalized regression neural networks for evapotranspiration modelling. *Hydrological Sciences Journal* 2010; 51(6). ISSN: 2150-3435.
13. Ahmed O, Mitchell J, Sanford K. Feedforward-feedback RV AC Controller using General Regression Neural Network (GRNN). FAC Artificial Intelligence in Real-Time Control, 1997.
14. Seela CR, Ravisankar B, Raju BMVA. A GRNN based frame work to test the influence of nano zinc additive biodiesel blends on CI engine performance and emissions. *Egyptian Journal of Petroleum* 2018; 27: 641-647.
15. Osamah AA, Garrouc AA. A general regression neural network model offers reliable prediction of CO_2 minimum miscibility pressure. *Journal of Petroleum Exploration and Production Technology* 2016; 6: 351-365.
16. Almalki YR. Implication of General Regression Neural Network (GRNN) for Wave Overtopping Prediction of Vertical Sea Defence. *International Journal of Advances in Mechanical and Civil Engineering* 2018; 5. ISSN: 2394-2827.
17. Islam MM, Gareth L, Hettiwatte SN. Application of a general regression neural network for health index calculation of power transformers. *Electrical Power and Energy Systems* 2017; 93: 308-315.