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Assessment of Optimum Neural Network Architecture in Forecasting and Mining Carbon

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Abstract—**Uncertainties in climate change have significant impacts on change in global temperatures having radiative forcing. The aerosols, emissions and concentrations from Green House Gases are the key drivers for such variations in the global climate. Carbon-dioxide is the most important anthropogenic Green House Gas having grown rapidly in the past three decades decreases the global energy. Carbon-dioxide is the most important anthropogenic Green House Gas having grown rapidly in the past three decades decreases the global energy. This paper presents an approach to determine the best performing Artificial Neural Network (ANN) algorithm for the forecast of carbon emissions from fossil fuels and flares and projects the emission rate. Various experiments are conducted to justify the swift, high performing, accurate and adaptive network amongst Simple Feedforward(FF), Multilayer Perceptron (MLP) with Backpropagation and Kohonen's Self-Organizing Maps(SOM) methods . The stability, convergence and prediction accuracy of all the above methods are analyzed with different learning rule, transfer function and weigh update methods and tested statistically. It is observed that among the three network models, the MLP with Gradient Descent Backpropagation learning method and Tangent hyperbolic transfer function has stabilized in lesser number of epochs with higher prediction rate. The experiment results depict the future impact of emissions and vulnerability in climate change.**

Index Terms—**Artificial Neural Network (ANN), Feedforward (FF), Green House Gases (GHG), Kohonen Self-Organizing Map (SOM), Multilayer Perceptron (MLP).**

I. INTRODUCTION

Climate change and our response to it are issues of global importance affecting not just agriculture and water resources but life itself. Apart from climate changes, due to natural causes, changes in the core of the earth or indiscrete use of hydro carbons all over the world, deforestation and other man made causes have resulted in global warming. The severity in climate change has to be mitigated for a socio-economic development producing a better human earth system [6]. Neural Networks are analytic techniques modeled after the processes of learning in the cognitive system and the neurological functions of the brain and capable of predicting new observations (on specific variables) from other observations (on the same or other variables) after executing a process of so-called learning from existing data [5].

Artificial Neural Networks (ANNs) learn from data examples presented to them in order to capture the subtle functional relationships among the non-linear data having complex structure and association[10]. This is in contrast to most traditional, empirical and statistical methods, which need prior knowledge about the nature of the relationships among the data. ANNs are thus well suited to model the complex behavior of most varying geotechnical engineering, medical diagnosis, financial forecasting and credit risk applications. Neural Networks facilitate nonlinear state space through function approximations in constructing a dynamic model with better prediction accuracy. It may be well suited to model load predictions and seasonality interacting with other components [1].

Many classification problems encompass the prediction of categorical or nominal scaled variable [7]. Neural Networks offers efficient modeling to solve complex problems in which there may be hundreds of predictor variables that may have many interactions [5].

A. ANN Architecture Selection

In this paper the performance and efficacy of non-linear predictive models are evaluated using supervised and unsupervised learning algorithms. Out of various network models available recurrent networks are used for pattern classification and Radial Basis Function (RBF) networks are applied for clustering a smaller group. Support Vector Machines (SVM) are able to solve classification problems and not suitable for function approximation. Principal Component Analysis (PCA) networks are appropriate for non-linear classifications using mixed mode learning [3].

Generalized Feedforward (FF) networks, Multilayer perceptron (MLP) networks and Self Organized Map (SOM) architectures are selected in this research, as they are efficient and appropriate for non-linear predictions. FF and MLP networks are driven by targets by adapting supervised learning and SOM network adjusts its weights and achieves the target using unsupervised learning. These three network models are experimented with respect to its learning rule, transfer function, number of epochs and weight update methods.

In order to improve performance, ANN models need to be developed in a systematic manner. Such an approach needs to address major factors such as the determination of adequate number of inputs, outputs, exemplars, processing elements and layers. The network architecture is further constructed with parameters that control the optimization, learning rule, transfer function and weight update methods. Preprocessing and normalization of data plays a major role in performance analysis of any network. Neural Network performance can be improved by modifying the learning

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parameters through a process called learning.

The carbon emission from Fossil-Fuel Burning, Cement Manufacture, and Gas Flaring are predicted for India using the above methods. Various statistical techniques are used to evaluate the success rate of the production set from different experiments. The robust outcome of the different networks and its prediction accuracy are tested with various performance error measures, statistics, best cost and epochs.

B. Impacts of Climate Change

With high rates of economic growth and over 15 percent of the world's population, India has become a significant consumer of energy resources and holding the third position in emissions having 4.7 lakh tons carbon emissions per year according to the latest statistical reports from the Carbon Dioxide Information Analysis Center (CDIAC) [2]. Hence it is inevitable to monitor the Carbon emission targets and reduce the adverse effects of climate change. Warming of the climate system is unambiguous, and has increased about 80% in the past decade which is nearly twice than that of the previous hundred years [4].

The insulating effect of certain gases in the atmosphere allows solar radiation to warm the Earth. They are the Natural and Industrial gases that trap heat from the earth. These gases are called as Green House Gases (GHG). Atmospheric concentrations of GHG are increased in emissions of Carbon-dioxide (CO2), methane (CH4), nitrous oxide (N2O) and halocarbons. The radiative forcing of the GHG is dominated by the Carbon dioxide which is represented as 77% of total anthropogenic GHG emissions [11]. The Global Carbon Project projected that the Emissions rose by 29% between 2000 and 2008. [12].

Governments at a 1997 UN Framework Convention on Climate Change in Kyoto, Japan, agreed legally binding commitments on greenhouse gas emissions. Industrialized countries agreed to reduce their combined emissions to 5.2% below 1990 levels during the five-year period 2008-2012 which was globally known as Kyoto Protocol [3].

Intergovernmental Panel on Climate Change (IPCC) presented the annual report in Copenhagen Summit, 2009 and findings assessed by Working Group I stated that the reason for increase in global average temperature is due to GHG concentrations [11].

India's 2006 total fossil-fuel CO2 emissions rose 6.1% over the 2005 level to 412 million metric tons of carbon. From 1950 to 2006, India experienced dramatic growth in fossil-fuel CO2 emissions averaging 5.8% per year and becoming the world's fourth largest fossil-fuel CO2-emitting country [6].

C. Prediction using ANN

Today, Artificial Neural Network models are being used in various research and application domains for prediction purposes. For hydrological problems, ANN models are used for prediction of tornados, damaging winds, thunderstorms, river flow and wind speed. Backpropagation neural networks used for prediction of rain fall data provide acceptable accuracy [5].

An ensemble procedure with neural network model was constructed by R.knutti, T.F Stocker, F.Joos, G.K. Plattner for climate change projections, resulting climate sensitivity, radiative forcing, future warming and weakening of sea levels in 2003 [9].

M.S. Rabinovitz, V. Krasnopolsky, A. Belochitski developed ensemble of Neural Network emulations for climate model physics to reduce the impact on climate simulations. Using neural networks the accuracy of climate simulations are improved significantly by reducing the systematic and random interpolation error and reducing the magnitudes of the extreme errors or outliers [8].

Energy consumption predictor for greenhouses from a MLP neural network was developed by Mario Trejo Perea et al. using real data obtained from a greenhouse located at the Queretaro State University, Mexico. The results showed that the selected ANN model gave a better estimation of energy consumption with a 95% significant level [7].

This paper is organized as follows. In Section II ANN algorithm experiments and research techniques are described. Section III depicts the statistical analysis and section IV states the findings from the research. Finally, conclusions are drawn in section V.

II. EXPERIMENT

A. Data Source

National CO2 emissions from fossil fuel and other industrial processes were calculated by the Carbon Dioxide Information Analysis Center of the US Oak Ridge National Laboratory. For the period 1950 to 2006 the calculations were based on United Nations Energy Statistics and cement data from the US ecological Survey.

The carbon emissions from Fossil fuels, Gas fuels, Liquid fuels, Solid fuels, Gas flaring, Cement production, Bunker fuels are taken for prediction along with per capita emission rate.

All emission estimates are expressed in thousand metric tons of carbon. Per capita emission estimates are expressed in metric tons of carbon.

B. Research Techniques

The objective of this research is to analyze the performance and efficacy of non-linear prediction models of Artificial Neural Networks using supervised and unsupervised learning methodologies. To identify the better prediction model with accuracy the carbon emissions data are forecasted for the years 2006-2020. The research is carried out with technical computing tool Matlab 7.1 with Neural Toolbox.

The most popular supervised learning neural models like Generalized Feedforward Techniques, Multilayer Perceptron with Backpropagation and unsupervised learning model like Kohonen Self Organizing Map are used to measure the effective success rate of the production set. The ANNs are trained with Gradient Descent, Backpropagation and Delta learning rules.

- The input variables, predictor variables were identified for the data analysis.
- The learning rule and required exemplars were selected for processing the network.
- Various training parameters and weight updation methods were specified for training the network.

- The activation function and validation procedure were selected for training the network.
- The termination criteria for the network were selected either based on number of epochs or based on the various performance measures like error levels and best cost.
- Testing was performed to compare the network output with the desired output.

1) Learning Rules

The neural network is initially trained using Gradient Descent (GDM) learning rule. The learning speed of the network depends on the step size and it oscillates if the momentum step size is too large. The Momentum provides the gradient descent with some inertia, so that it tends to move along a direction that is the average estimate for down.

The delta rule minimizes the mean squared error in the output unit and propagates backward to derive the hidden units of the network, since the target values for the hidden units are unknown. The set of values of weights that minimizes the mean squared error is what is needed for the next cycle of operation of the neural network.

The Quickprop algorithm without hidden nodes and with direct connection between the input layer and the output layer are also used in the third method. Hidden nodes are added randomly at a time. At the time new hidden nodes are added to the network, their connections with the inputs are frozen and only their output connections are trained using the Quickprop algorithm. This process is stopped when the model performance shows no further improvement learning methodologies and the (MSE) approaches zero.

Increasing the learning rate parameter will decrease the training time, but will also increase the possibility of divergence, and of rattling around the optimal value.

2) Transfer Functions

Transfer functions do the final mapping of the activations of the output neurons into the network outputs. But the outputs from a single cycle of operation of a neural network may not be the final outputs, as further iterations of the cycles are required till the convergence is attained. Hyperbolic tangent function, sigmoid and linear functions are used along with the different learning methods. Hyperbolic tangent functions are fast and straightforward to implement. Sigmoid functions are continuously differentiable and hard to implement. Linear functions are very simple and used for small set of data.

During the training process the initial, final and best weights are stored and the weight update method is given as a parameter as online / batch. The input and output data are normalized and tested with the desired data. The production set is plotted on the screen and all statistical measures are displayed to evaluate the accuracy, stability, convergence and success rate of the production set.

3) Weight Updation Methods

Online weight update method updates weights after every exemplar / pattern presentation. Batch method updates the weight after every epoch of training. Custom method updates weight depending on the user's input. Since the weight correction is dependent upon the performance surface characteristics and learning rate, to obtain constant learning, an adaptive learning parameter is necessary

C. Network Architecture Parameters Specifications:

Eight non-linear emission parameters from the period of 1950-2006 are preprocessed randomly. Out of which 10 years exemplars are specified for testing and remaining 47 years exemplars are provided for training. The production output was generated from 2007-2020.

Input Processing Elements	:	1
Output Processing Elements	:	8
Exemplars for training	:	47
Number of Hidden Layers	:	1
Hidden Layer Processing Elements	:	8

Training process of the network was carried out to learn from the input and to obtain optimal values for different network parameters. Validation procedures, Activation functions and termination criteria for network are also supplied for network execution. The output from all experiments are recorded and statistically tested to identify a suitable and swift network model having better prediction accuracy.

C. Experimental Performance & Results

The following table depicts various Neural Network architectures pertaining to supervised and unsupervised learning that are used for the experiment. The learning rule, transfer function, number of epochs, weight update method and stopping criteria for the network are tested with various inputs.

By using the above architectures and different learning rules the carbon emissions from different sources are predicted. In order to find the best algorithm the following statistical techniques are applied.

III. Statistical Analysis

In the output production set the correlation between the year to emissions and normalized MSE were almost similar.

In order to find the significant difference between the above network models the following tests are conducted.

A. Correlation

Correlation coefficient between two measurement variables is calculated to observe the relationship and measurements on each variable for N subjects. In our experiments correlation between year and emission rates are calculated. The correlation coefficients for all experiments are displayed below.

The following graph depicts the correlations obtained from different neural models.

By observing the above graph it is obvious that MLP1 experiment has the best correlation among all other experiments conducted.

TABLE I: NEURAL NETWORK ARCHITECTURES AND ITS SPECIFICATIONS

Neural Architecture	Experiment Number	Learning Rule	Transfer function	Stop Criteria	Weight update
Multilayer Perceptron with Back propagation	MLP1	Momentum-GDM	Tanhaxon	Max 1000 epochs / minimum gradient	Batch
	MLP2	Delta	Sigmoid	MSE termination	Online
	MLP3	Quickprop	Linear axon	MSE termination	Custom
Generalized Feedforward	GFF1	Momentum-GDM	Tanhaxon	Max 1000 epochs / minimum gradient	Batch
	GFF2	Delta	Sigmoid	MSE termination	Online
	GFF3	Quickprop	Linear axon	MSE termination	Custom
Kohonen's Self Organizing MAP (SOM)	SOM1	Momentum-GDM	Tanhaxon	Max 1000 epochs / minimum gradient	Batch
	SOM2	Delta	Sigmoid	MSE termination	Online

TABLE II CORRELATION BETWEEN YEAR AND OUTPUT

Experiment	Correlation
GFF1	0.974
GFF2	0.976
GFF3	0.877
MLP1	0.988
MLP2	0.977
MLP3	0.982
SOM1	0.873
SOM2	0.860

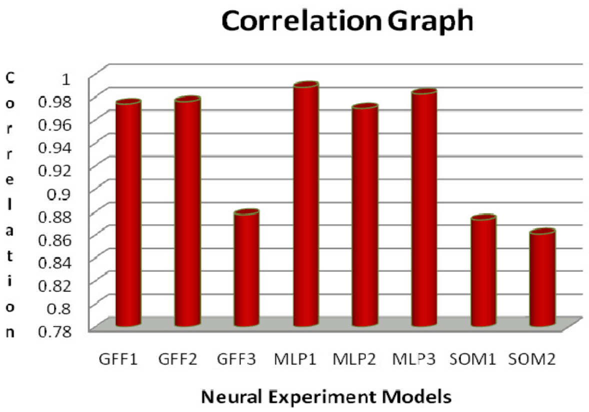

FIG. 1: Correlation between Year and Emissions

B. *Analysis of Variance (ANOVA):*

As the statistics of all the above eight experiments were similar, the variance of output production set were analyzed to test the hypothesis that each algorithm is drawn from the same underlying probability distribution (H0) against the alternative hypothesis that underlying probability distributions are not the same for all algorithms (H1). The hypothesis test is defined below.

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8$$

$$H_1 : \mu_i \neq \mu_j \qquad i, j = 1,2,3 \ldots 8 \text{ and } i \neq j$$

where μ_1 , μ_2, μ_3.. μ_8 are average variance values obtained from each experiment. Totally eight experiments are conducted with 8 input parameters having carbon emissions as common source of variability. Hence one way ANOVA is used. Total number of Observations (N) = 64 and Sample Size (K) = 8. The following tables depict the summary and output of Analysis of Variance of different neural algorithms.

The F-value obtained F(7,56) = 2.17482 from the above ANOVA table. Since the calculated value (23.9723) > Table value (2.1782) with a significant level of α = 0.05, the Hypothesis H0 has been rejected and Hypothesis H1 is accepted. So using the ANOVA table it is proved that the probability distributions are not same for all algorithms and the results obtained from different experiments differ significantly.

In order to find the best suitable algorithm for the measure of prediction accuracy the following statistics have been calculated and evaluated.

TABLE III : ANALYSIS OF VARIANCE (ANOVA) TABLE FOR COMPARISON OF NEURAL EXPERIMENT'S PRODUCTION SET

SUMMARY

Groups	Count	Sum	Average	Variance
MLP1	8	1.62592E+09	2.03240E+08	1.16198E+16
MLP2	8	1.09579E+06	1.36974E+05	2.86308E+09
MLP3	8	5.24579E+07	6.55723E+06	9.47732E+12
GFF1	8	8.48309E+08	1.06039E+08	3.62019E+15
GFF2	8	5.47666E+04	6.84582E+03	7.98155E+07
GFF3	8	1.21450E+07	1.51812E+06	1.55397E+12
SOM1	8	5.14647E-04	6.43309E-05	7.32102E-10
SOM2	8	7.65790E+05	9.57238E+04	1.00426E+10

ANALYSIS OF VARIANCE (ANOVA)

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Sum of Squares(MSS)	Variance Ratio (F)	P-value	F criteria (α=0.05)
Between Groups	3.1990E+17	7	4.5700E+16	23.9723	1.03E-14	2.1782
Within Groups	1.0675E+17	56	1.9063E+15			
Total	4.2666E+17	63				

C. Statistical Review

Various performance measures like Mean Squared Error (MSE), Normalized MSE, percent error and best cost of every experiment is observed for the analysis. MSE is the mean of the squared error between the desired output and the actual output of the neural network.

The mean squared error is computed as follows.

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{N \quad P}$$

Where P = number of output processing elements (8)
N = number of exemplars in the training data set
(47)
yij = estimated network emissions output for exemplar i at processing element j
dij = actual output for emissions exemplar i at processing element j

NMSE calculates normalized coefficients automatically from the network components and computes the mean squared error between the actual and desired datasets.

$$NMSE = \frac{P \quad N \quad MSE}{\sum_{j=0}^{P} \frac{N\sum_{i=0}^{N} d_{ij}^2 - (\sum_{i=0}^{N} d_{ij})^2}{N}}$$

Where P = number of output processing elements (8)
N = number of exemplars in the training data set
(47)
MSE = Mean Squared Error
d_{ij} = actual output for emissions exemplar i at processing element j

Percent error is calculated as error percent between the desired output and the actual output obtained from the network.

$$\%\,Error = \frac{100}{N \quad P}\sum_{j=0}^{P}\sum_{i=0}^{N}\frac{|\,dy_{ij} - dd_{ij}\,|}{dd_{ij}}$$

Where P = number of output processing elements (8)
N = number of exemplars in the training data set
(47)
dy_{ij} = denormalized network emissions output for exemplar i at processing element j
dd_{ij}= denormalized desired network emissions output for exemplar i at processing element j

The Best cost calculates the minimum error obtained for the training and minimizes the maximum deviation between the desired output and net output.

From the above performance measures table and graphs it is evident that MLP1 network model is having fewer errors and better production set. Hyperbolic function with Gradient Descent learning rule works better for data prediction.

Experiment MLP3 with Quickprop learning rule and linear transfer function also improved in data prediction. Generalized Feedforward networks are also producing satisfactory results with fewer errors. Self organizing maps could not perform well as it is more appropriate in high dimensional data space for classification and clustering problems.

TABLE IV: SUMMARY OF STATISTICS FOR NEURAL ARCHITECTURES

Experiment Number	Mean Squared Error	Normalized Mean Squared Error	Percent Error	Best Cost
MLP1	0.2511	0.0018	1.1793	0.0035
MLP2	2.7548	0.0199	15.2861	0.0043
MLP3	0.7085	0.0051	6.5843	0.0145
GFF1	4.1308	0.0131	16.4333	0.0026
GFF2	11.5182	0.0365	16.1511	0.0046
GFF3	10.7972	0.0341	23.2887	0.0052
SOM1	1.5170	0.1260	17.5465	0.0241
SOM2	18.1760	0.8908	21.3456	0.0321

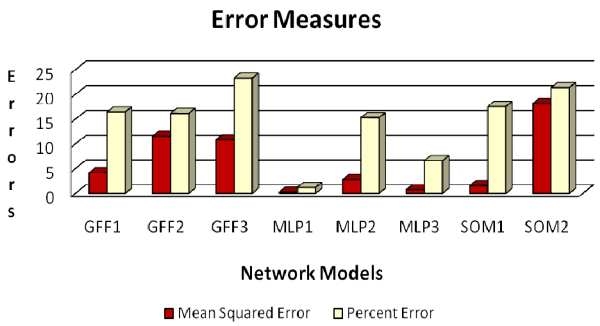

Fig. 2: Error Measures Graph

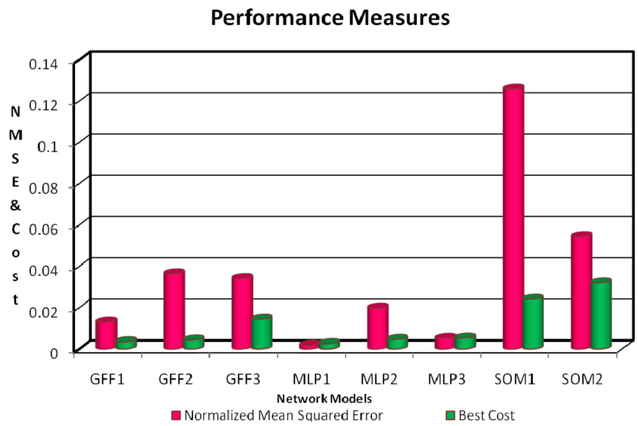

Fig. 3: Performance Measures Graph

IV. FINDINGS

Artificial Neural Networks programs implement sophisticated pattern detection and machine learning algorithms to build predictive models from large historical databases. Neural networks are an attempt to mathematically describe the functioning of neurons and therefore to model some features of the human brain in prediction an ensemble approach was adapted in this study. Several algorithm characteristics can be deduced from the experiments described above.

In all the above experiments, networks using GDM momentum and tangent hyperbolic functions reached the minimum MSE only at the 1000th epoch. The network needs more number of epochs to become stable. But the network model has good computational capability with better prediction rate.

By adapting delta learning rule with sigmoid activation functions all networks stabilized within 20 epochs, but the error rate of the production set were quite high.

Networks using Quickprop learning rule with linear activation functions were stabilized within 150 epochs with moderate error rate.

MLP with Backpropagation networks had a higher learning rate with better prediction accuracy. The error rates were also minimal. Although it takes more number of epochs to learn, the output production set was accurate yielding the best results.

Feedforward networks are simple to use and they are generalizations of MLP. They solve the problems efficiently using function approximation techniques and not suited for the prediction problems. In some applications it is better to have slow convergence as the early stopping may lead to inconsistent results.

The results of the SOM networks were not satisfactory and the optimization of the training could not be achieved within the specified number of epochs. Self Organizing Map usually requires more storage and data for self learning. It performs well with high dimensional data in function approximation as it learns through the nearest neighborhood relation.

Increasing the learning rate parameter will decrease the training time, but will also increase the possibility of divergence, and of rattling around the optimal value.

In general, on prediction problems, for networks that contain up to a few hundred weights, the gradient descent learning rule with optimum momentum and tangent hyperbolic functions performs better.

The following graphs depict the estimated production set of emissions from Fossil fuels, Liquid fuels, Solid fuels, Gas fuels, Cement Production, Bunker fuels, Gas flaring from the year 2007 to 2020 using MLP with Backpropagation. All emission estimates are expressed in thousand metric tons of carbon. Per capita emission estimates are expressed in metric tons of carbon.

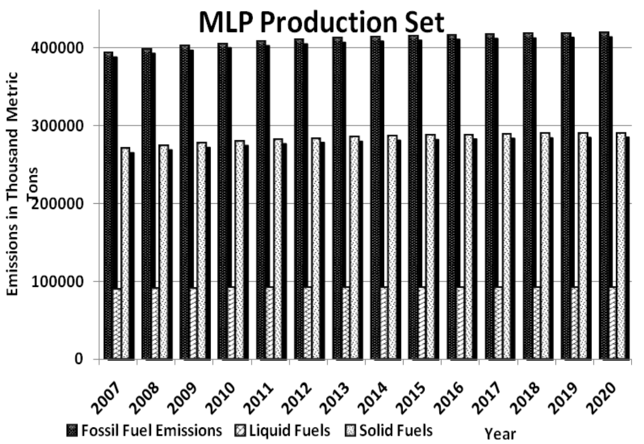

Fig. 4: Multilayer Perceptron's Carbon Emission from fuels Production set from the year 2007 to 2020

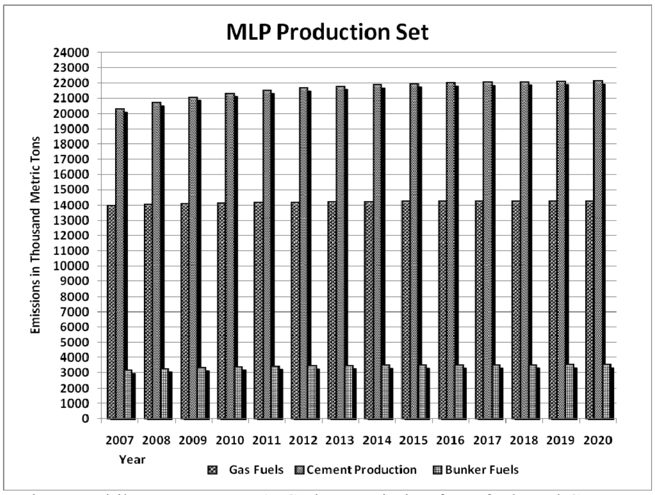

Fig.5: Multilayer Perceptron's Carbon Emission from fuels and Cement Production set from the year 2007 to 2020

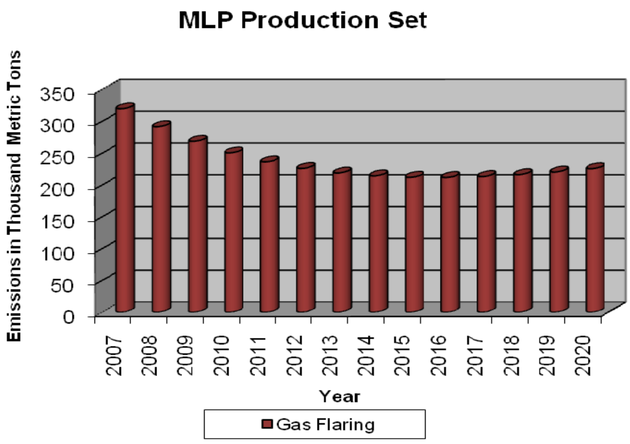

Fig.6: Multilayer Perceptron's Carbon Emission from Gas Flaring Production set from the year 2007 to 2020

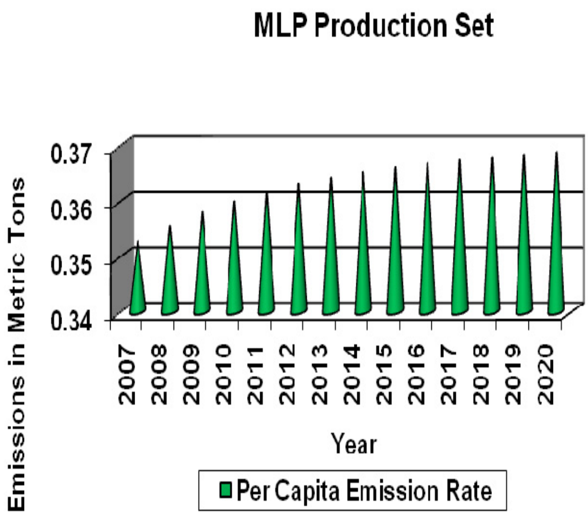

Fig. 7: Multilayer Perceptron's Per Capita Carbon Emission rate Production set from the year 2007 to 2020

Projected increase in carbon emissions by the year 2020 is plotted below.

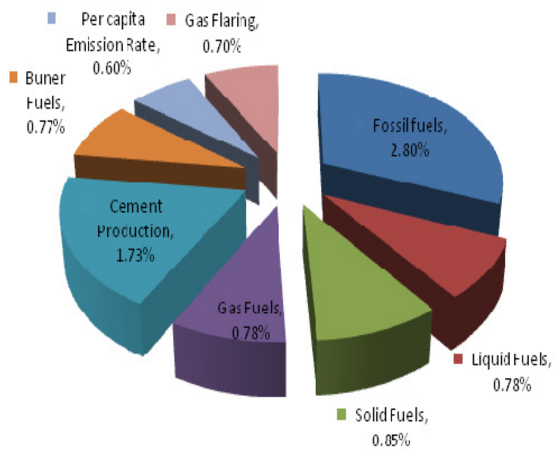

Fig. 8: Projected Increase in Carbon Emission by the year 2020

According to the results obtained from our experiments better forecasting network the general emissions from fossil fuels have 2.8% increase and emissions from cement production have an increase of 1.7% by the year 2020. The remaining fuel emissions and flaring emissions have an increase of 0.7% approximately.

V. CONCLUSION

The performance of neural networks in approximating functions is used in this research to predict a climate response due to emissions from selected input parameters, without explicitly integrating the climate model.

Best networks are the ones which give minimum training error. The output error depends intrinsically on the cost function used, but the criterion does not say how errors are propagated inside the network model. The network performance varied depending on the stopping criterion, weight updation, learning rule and number of epochs.

This research reveals the prediction capacity of artificial neural networks using carbon emissions data. The assessment of accuracy for different neural network models have been compared and analyzed based on its variance, error rates and correlation coefficient between the actual and the expected to see how close the prediction is to its true outcome.

By the analysis done above, we observed that the MLP with Backpropagation is better than the other two neural models. It has the best prediction accuracy and less error rate because when linear data is given as input, it allows higher learning rates to maintain stability.

The impacts of all emissions and climate change can be reduced, delayed or avoided by implementing significant mitigation policies in all sectors. The widespread diffusion of low-carbon technologies may take many decades. If early investments in these technologies are made attractive, the risks and exposure to vulnerability from extreme climate change can be managed for a radiant future.

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