REPORT

Coding assignment 1

Predicting NOx emissions from gas turbines

SUBMITTED BY

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INTRODUCTION

A multilayer feed-forward artificial neural network with back propagation algorithm has been used to predict the NOx gas emissions form gas turbines.

The dataset contains 1000 instances of 10 sensor measures aggregated over one hour (by means of average or sum) from a gas turbine located in Turkey's north western region for the purpose of studying flue gas emissions, namely NOx (NO + NO2).

The dataset was obtained from data article “Predicting NOx emissions from gas turbines” by, Heysem Kaya, Department of Information and Computing Sciences, Utrecht University, 3584 CC, Utrecht, The Netherlands.

It is important to monitor the NOx pollutants emitted during combustion operations in a power plant. To this end, three solutions are developed to monitor flue gas emissions from a combustion unit: i) periodic measurements, ii) continuous emission monitoring system (CEMS), or iii) predictive emission monitoring system (PEMS), respectively. Predictive emission monitoring systems (PEMS) are important tools for validation and backing up of costly continuous emission monitoring systems used in gas-turbine-based power plants. Their implementation relies on the availability of appropriate and ecologically valid data.

So an artificial neural network was developed to predict the NOx gas emissions from gas turbines for which the 9 inputs each for 1000 patterns are obtained from the dataset obtained from the published journal. And the result obtained from the neural network created was compared with the target values provided in the report itself.

DATA DESCRIPTION

The dataset is composed of hourly average sensor measurements of eleven variables (nine input and one target variables). There are a total of 36,733 instances collected over 5 years. A subset of this dataset (1000 instances) has been taken for analysis purposes. The nine input measurements (independent variables) can be grouped into two as ambient variables (e.g., temperature, humidity, pressure) and process parameters (e.g., turbine energy yield, air filter difference pressure). The names, abbreviations and basic statistics of the variables used in the study are summarized in Table 1. The data are collected in an operating range between partial load (75%) and full load (100%).

Variable	**Abbr.**	**Unit**	**Mean**
Ambient temperature	AT	°C	17.71
Ambient pressure	AP	mbar	1031.07
Ambient humidity	AH	%	77.87
Air filter difference pressure	AFDP	mbar	3.93
Gas turbine exhaust pressure	GTEP	mbar	25.56
Turbine inlet temperature	TIT	°C	1081.43
Turbine after temperature	TAT	°C	546.16
Compressor discharge pressure	CDP	mbar	12.06
Turbine energy yield	TEY	MWH	133.51
Nitrogen oxides	NOx	mg/m	65.29

Table 1

METHODOLOGY

From the 1000*10 dataset , it’s been left upto the user to decide what fraction of the dataset is used for training and the rest is used for testing. The no. of inputs fed into the network can also be modified on prompt by the user. Same goes for the number of hidden neurons.

The result obtained is compared with target output provided in the dataset and analysis is done using calculating the mean square error for the training and test set separately.

The final output of the neural network is stored to a file and an array of error is created to analyse the performance of the neural network.

A plot is created between the MSE value and the number of iterations.

The optimal number of hidden layers, learning rate, momentum rate was found by trial and error method using the above mentioned error analysis.

NUMBER OF HIDDEN NEURONS (H)	LEARNING RATE	MSE (Training set)	MSE (Test set)
2	0.01	0.0027	0.0052
2	0.05	0.0061	0.0073
2	0.1	0.0024	0.0044
2	0.5	0.0062	0.0063
5	0.01	0.0036	0.0114
5	0.05	0.0020	0.0025
5	0.1	0.0020	0.0025
5	0.5	0.0023	0.0067
10	0.01	0.0032	0.0047
10	0.05	0.0014	0.0035
10	0.1	0.0015	0.0034
10	0.5	0.0015	0.004
20	0.01	0.002	0.0023
20	0.05	0.0019	0.0024
20	0.1	0.0014	0.0017
20	0.5	0.039	0.0279

Total no. of iterations = 10000

No. of training patterns = 699

No. of testing patterns = 300

Momentum coefficient = 0.6

The MSE for training and MSE for testing varied in the range of 0.0013 to 0.01, but no definitive pattern was obtained that could ascertain the optimum value of learning rate and no. of hidden neurons to be used. The variation in the value of MSE could be attributed to the randomisation used in the code. It was observed that for 20 hidden neurons and learning rate 0.5, erroneous results were obtained. Consistently good results were obtained when 10 hidden neurons were used (concluded on the basis of actual difference in the predicted output and actual output).

RESULTS AND DISCUSSION

Parameters:

- NUMBER OF HIDDEN NEURONS = 10
- LEARNING RATE = 0.05
- PERCENT OF TESTING PATTERN IN DATASET : 30 %

Results:

MSE (training) : 0.0014

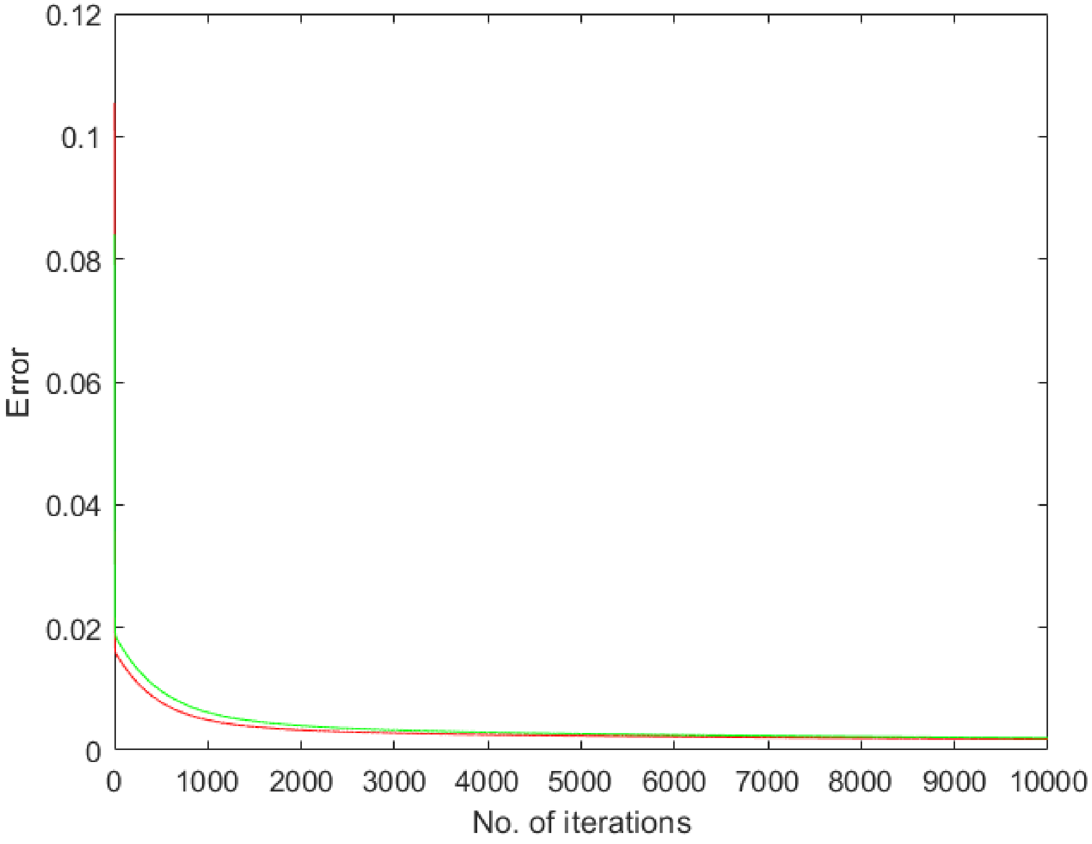
MSE (testing) : 0.0137

Error in prediction (First 8 entries are considered) :

Actual Output	Predicted value	Error in prediction (abs)
74.4840	70.9130	3.5710
82.0950	81.6866	0.4084
82.3810	80.2449	2.1361
66.5370	66.2031	0.3339
80.4420	81.4041	0.9621
87.6760	84.6943	2.9817
81.4600	82.4419	0.9819
75.7060	75.5174	0.1886

Table 2

Plot of error vs iterations (training , testing):



CONCLUSIONS

- The result of the network is highly dependent on the dataset i.e. if the target values are of the same order then error obtained was less.
- No definitive pattern was obtained that could ascertain the optimum value of learning rate and no. of hidden neurons to be used.
- The test set error (MSE) is always larger than the training set error.
- No significant change in the results with variation in the number of iterations.
- The results vary time to time and can be attributed to the random initialization of connection weights and random sorting of patterns initially.
- Use of momentum terms has increases convergence rate.
- Normalization and randomization of the input data improve the outcome of the neural network.
- Use of more input neurons increases accuracy and decreases MSE.