



Data from Predictive Emission Modules Implemented on GE-LM1600, GE-LM2500 and RR-RB211 Gas Turbines Employed in Natural Gas Compressor Stations

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Abstract

Predictive Emission Monitoring (PEM) models have been developed for three gas turbine engines employed in natural gas compressor stations on TransCanada, Alberta System. These are RR-RB-211, GE-LM2500 and GE-LM1600, all non-DLE units. The PEM models are based on an optimized Neural Network (NN) architecture which takes 4 or more fundamental engine parameters as input variables. The model predicts NO_x emission in ppmv-dry-O₂ corrected and in kg/hr. The NN models were trained using Continuous Emission Monitoring (CEM) measurements taken at each station and comprising several sets of actual emission data collected over the four seasons of the year where ambient temperatures were vastly different (-20 °C to +20 °C). These training data were supplemented by other emission data generated by Cycle Deck tools to generate emission data at different ambient temperatures ranging from -30 to +30 °C. The outcome is emission data of engine emissions at different operating conditions covering the range of the engine operating parameters from minimum to maximum loads. The PEM models comprise simple single layer perceptron type NN with only two neurons in it. The performance of the NN-based model showed a correlation coefficient greater than 0.99, and error standard deviation of 4.5 ppmv of NO_x and 1.4 kg/hr as NO₂. Uncertainty analysis was conducted to assess the effects of uncertainties in the engine parameters on the NO_x predictions by PEM. It was shown that for uncertainty in the ambient temperature of +1 °C, the uncertainty in the NO_x prediction is + 0.9-3.5%. Uncertainties of the order of +1% in the other three input parameters results in uncertainties in NO_x predictions (ppmv or kg/hr) by ±2.5 to ±6%. Data from the implemented PEM models on the three aforementioned gas turbines were collected over a period of one year and compared with AP-42 emission factors. Results of these comparisons are summarized.

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1. Introduction

The EPA publishes emission factors for gas turbines in its Compilation of Air Pollutant Emission Factors, Volume I Stationary Point and Area Sources, EPA (Environmental Protection Agency) Publication No. AP-42 [1]. The document has been published since 1968 as the primary compilation of EPA's emission factor information. Government regulatory agencies, industry and others use the document to estimate emissions of atmospheric pollutants, a critical step in the development of effective air management strategies.

In Canada, actual NO_x emissions from the pipeline industry are generally not accurately determined since CEM systems are not required on compressor drivers. As an alternate method to quantify the NO_x emission from small-to-medium size gas turbines typically used in pipeline systems, a PEM system can be easily developed to provide a better and a credible estimate of NO_x emissions from these engines at all loads and at prevailing ambient conditions. Once integrated on a yearly basis, a PEM system would provide a better estimate of the NO_x emissions from these engines compared to typical estimation methodologies that rely on the AP-42 emissions factors.

Current technologies related to NO_x emissions have advanced rapidly in the past few years to the point that PEM models are now generally accepted for gas turbine applications and are in compliance with CFR Parts 60 and 75 [2,3]. These are shown to offer greater accuracy [4,5] and faster response time (in terms of downtime avoidance) than CEM techniques. They can also provide advance results for a specific set of operating conditions [6-9].

Hung's work on predicting emissions from gas turbines [10] indicates that too much emphasis has been placed on modeling chemical kinetics and not enough on the physical processes of combustion. By and large, NO_x formation was based on finite-rate reaction kinetics and the widely accepted Zeldovich mechanism [11]. Subsequent revisions to the model incorporated a number of features, including the effects of ambient humidity and temperature, water injection, synthetic coal gas combustion and fuels containing nitrogen in the combustor [12].

Several empirically developed correlations to predict NO_x emissions are listed in [13-15] with combustor pressure, overall fuel-air ratio, combustor inlet temperature, combustor air flow rate and residence time as input variables. These correlations are very useful when applied to specific machines, specific fuels and under specific operating conditions. Recent efforts attempted to improve accuracy of semi-empirical correlations through optimization methods [16-19].

In the present study, emission prediction models have been developed based on an optimized Neural Network (NN) architecture that takes 4 fundamental engine parameters as input variables, and predicts NO_x as an output variable. The paper will first describe the model development demonstrated on a GE-LM1600 gas turbine employed in natural gas compressor station on the TransCanada Pipeline System in Alberta, Canada. Here, the NN is trained using two sets of actual emission tests conducted on the gas turbine. A total of 387 tests were conducted on two different dates, and at different operating conditions covering the range of the engine operating parameters (see Appendix A). This set of data was supplemented by 'Cycle-Deck' data generated by a NO_x prediction module developed by GE (see Appendix B). The technique is the same as that followed in developing a PEM module for an RR-RB211-24C engine reported in [20] and for a GE-LM2500 reported in [21]. Data from the implemented PEM models on the aforementioned three gas turbines were collected over a period of one year and compared with AP-42 emission factors.

2. AP-42 Emission Factors

AP-42 Chapter 3.1 [1] uses an emission factor which is a representative value that attempts to relate the quantity of a pollutant released to the atmosphere with an activity associated with the release of that pollutant. For natural gas-fired gas turbines, these factors are usually expressed as the weight of pollutant per unit fuel volume burned or its equivalent heating value (e.g. kg/m³ or kg/GJ). Such factors facilitate estimation of emissions from various sources of air pollution. In most cases, these factors are simply averages of all available data of acceptable quality, and are generally assumed to be representative of long-term averages for all facilities in the source category.

Emission factors in AP-42 Chapter 3.1 have been determined from gas turbines with no add-on control devices (*uncontrolled*) as well as from *controlled* engines. There are three generic types of emission controls in use for gas turbines, wet controls using steam or water injection to reduce combustion temperatures for NO_x control, dry controls using advanced combustor design to suppress NO_x formation and/or promote CO burnout, and post-combustion catalytic control to selectively reduce NO_x and/or oxidize CO emissions from the turbine [1]. Other recently developed technologies promise significantly lower levels of NO_x and CO emissions from diffusion combustion type gas turbines. These technologies are currently being demonstrated in several installations. Note that the emission factor (EF) of NO_x for an uncontrolled engine is:

All Loads:

EF = 0.127 kg/GJ (0.295 lb/MMBtu) – based on HHV

Loads greater than or equal to 80%:

EF = 0.139 kg/GJ (0.32 lb/MMBtu) – based on HHV

3. CEM Measurements

Field measurements were taken to determine the variation of emission levels from an GE LM1600 gas turbine used at a natural gas compressor station on the TransCanada Pipeline System in Alberta at various loads, i.e., engine power output. The tests were performed on two different dates and at different operating conditions covering the range of the engine operating parameters. The levels of NO_x, CO, CO₂, O₂ and moisture in the exhaust stack were measured by CEM [22] using instruments and on-site calibration techniques approved by the U.S. EPA [23], i.e.:

- Carbon Monoxide- EPA Method 10
- Oxides of Nitrogen –EPA Method 7E
- Carbon Dioxide –EPA Method 3A
- Oxygen –EPA Method 3A
- Total Hydrocarbons –EPA Method 25

The moisture content is measured according Alberta Environment Method 4 [24].

In particular, the NO_x measurements were made with an approved chemiluminescent continuous analyzer. These measurements were broken down to total NO_x and NO component, both in ppm by volume (dry and corrected to 15% O₂). The uncertainty in the measurements of NO_x is typically <2% of calibration span of the analyzer.

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Pertinent engine performance parameters and ambient conditions at the site were obtained from the station data acquisition system. These parameters were: ambient temperature, the engine shaft speed (N1), air compressor discharge pressure (P3) and fuel gas flow rate (Qf), i.e., a total of **four** engine parameters. Gas samples were also taken to determine the composition of the natural gas used for fuel gas (Table 1).

Table 1: Mixture Composition of the Fuel Gas.

	Mole %
METHANE	91.387
ETHANE	5.025
PROPANE	1.418
i-BUTANE	0.166
n-BUTANE	0.223
i-PENTANE	0.051
n-PENTANE	0.039
C6+	0.045
Helium	0.033
NITROGEN	0.679
CARBON DIOXIDE	0.934
Total	100.00

For each test point, the engine speed was adjusted to reach the desired power output. The engine was allowed to stabilize over a twenty-minute period before the engine condition was changed. The unit load was varied from roughly 33 percent to maximum load to give several operating points on each test date. Results of these tests along with the pertinent gas turbine parameters are given in Appendix A. Emissions in terms of NO_x (in ppm-dry-15%O₂ corrected and in kg/hr) are plotted in Figs. 1 and 2 vs. fuel consumption, respectively. The variations in the NO_x emission for a given fuel consumption is due to variations in the ambient conditions, engine speeds and output shaft power. The overall trend of increasing NO_x with increasing load (and hence Qf) is due to the higher temperatures in the combustor, which leads to additional NO_x via the thermal mechanism. These higher combustor temperatures result from higher compressed air temperatures and lower air-to-fuel ratios as the unit load is increased.

The above data were supplemented by a set of data generated by a ‘Cycle-Deck’ prediction tool developed by GE to cover ambient temperatures outside the range of those of the actual CEM tests. The temperature range considered was from -30 °C to + 30 °C at an increment of 10 °C. The generated data are given in Appendix B and are also plotted in Figs. 1 and 2. It is shown that the GE ‘Cycle-Deck’ generated data are in line with those obtained from the actual CEM tests. A statistical generated noise around these data points of a standard deviation= 0.5% was applied to each of the input and output variables in order to increase the number of data points to match that of the number of measured data point so as to balance the influence of the two sets. Both sets of data, i.e. the CEM measured data set and the ‘Cycle-Deck’ generated data are then used in the training the NN based PEM model described in the following Section. Training NN is the most crucial and important step in NN-based PEM development and must be conducted with attention to the resulting accuracy and performance of the best or optimized NN architecture.

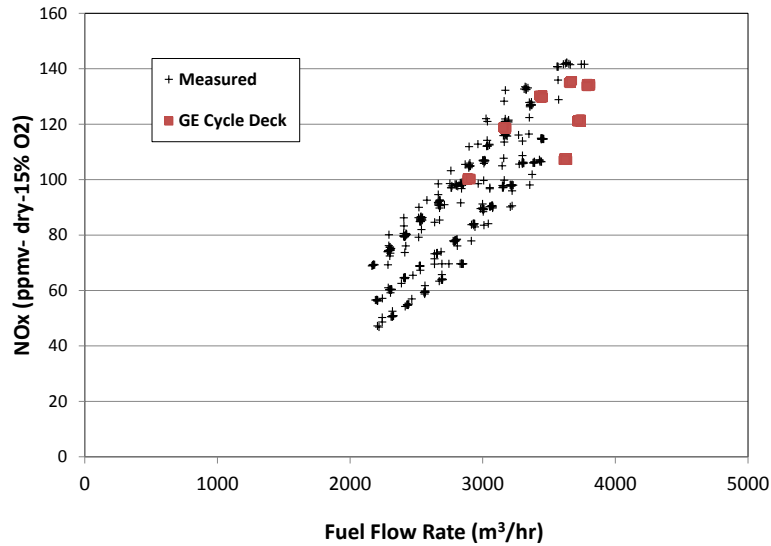


Figure 1: Measured and GE Cycle-Deck NOx Emission Data (in terms of ppmv-dry-15%O2).

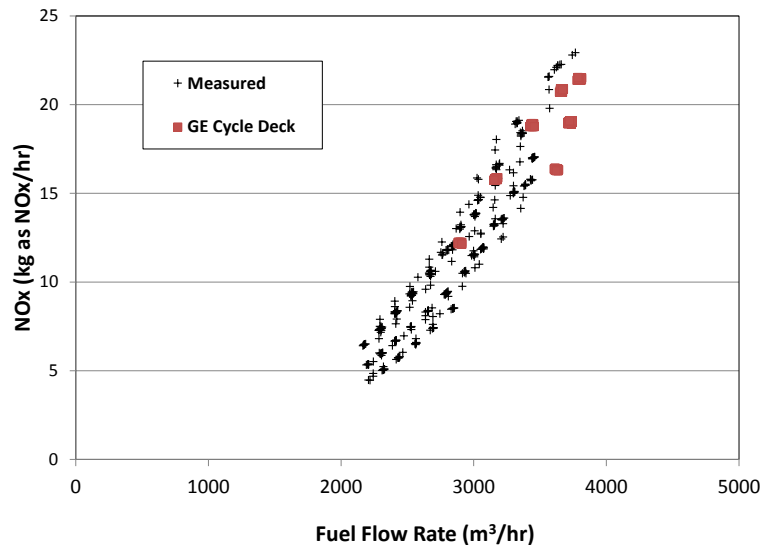


Figure 2: Measured and GE Cycle-Deck NOx Emission Data (in terms of kg/hr).

4. Neural Network Based PEM

Neural Network architecture was then developed as a basis for a PEM model. The input parameters are the four engine parameters identified, while only NO_x was taken as the output parameter (either in ppmv-dry-15%O₂, or in kg/hr). Three types of NN architectures were considered and the respective training algorithms were applied to the training set. These were: Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), and Generalized Regression NN (GRNN). These Networks were based on feed forward architectures with back-propagation optimization during training of the network [25]. In the case of MLP, the processing elements, called ‘neurons’, receive weighted sum of signals from neurons in the layer directly before it and send signals to the neurons in layer following it through a function called the activation function, using the following formulation:

$$Z_{k,i} = \Phi \left[\sum_{j=1}^{M(k-1)} w_{k,i,j} Z_{k-1,j} - B \right] \quad (1)$$

where

- k - layer number.
- i,j - neuron indices.
- $M(k)$ - total number of neurons in layer k .
- $Z_{k,i}$ - output of neuron i in layer k .
- $w_{k,i,j}$ - weight between neuron j in layer $k-1$ and neuron i in layer k .
- B - a threshold value.
- Φ - function to be applied at each neuron.

A variety of optimization techniques can be used to find the weights (w), the most common of which are the back propagation, conjugate gradient descent, and quick propagation techniques [25]. Several papers survey the various types of networks, describing their architecture, learning algorithms and applications, e.g., [26,27].

In the present work, the number of neurons in each hidden layer in each of the three structures mentioned earlier was varied, and overall normalized error was determined for each NN architecture. It was found that the simplest architecture with the least error was of an MLP type with one hidden layer of 2 neurons as shown in Fig. 3. All of the neurons in this architecture are of linear type, which perform a weighted sum of their inputs, biased by a threshold value (see Eq. 1). The activation functions are of a hyperbolic type, except for the input layer, consisting of the **four** neurons corresponding to the four input engine parameters shown, which was linear. The architecture’s weights and thresholds constitute the main fitting parameters for implementation in the PEM model.

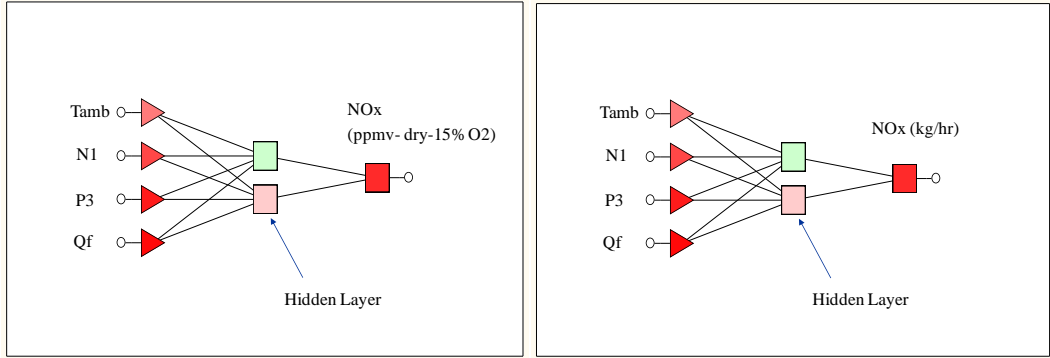


Figure 3: MLP Architecture for NOx Prediction.

Sensitivity analysis was then conducted to assess the influence of each of the four input parameters on the output parameter, i.e. the predicted NOx. Table 2 shows the results of this analysis in terms of ranking each parameter from highest (rank 1) to the lowest (rank 4). The criterion used in ranking is based on determination of the ratio of the network error if each input is eliminated sequentially to the overall network error when all inputs are present. Ratios close to or less than 1.0 indicates near-irrelevant inputs, while large ratios indicate particularly important input variables. It was found that, the fuel flow (Qf) is the highest sensitive parameter in so far as NOx prediction by this model. Training this network using the 1872 data points resulted in a good fit with a correlation coefficient greater than 0.98 as shown in Table 2. The standard deviation of the error in the prediction of NOx in terms of ppmv-dry-15% O2 is 3.9 ppmv, and in terms of kg/hr is 0.43 kg/hr. This should not be misconstrued as being the error of NN prediction; it is rather an indication of how well the NN has been trained to match the measured values.

Table 2: Training Performance and Sensitivity of the MLP Neural Network Architecture.

NOx (ppm)					
Ranking				Correlation Coefficient	Error S.D. (ppm)
Tamb	N1	P3	Qf		
2	4	3	1	0.9874	3.9

NOx (kg/hr)					
Ranking				Correlation Coefficient	Error S.D. (kg/hr)
Tamb	N1	P3	Qf		
3	2	4	1	0.9948	0.43

5. Results and Uncertainty Analysis

Figures 4 and 5 show the PEM results after training the NN and comparison with the actual data used in the training. Good agreement is demonstrated based on NO_x in terms of both ppmv and kg/hr). The corresponding error distribution as a function of fuel flow are shown in Figs. 6 and 7, which show that these error in NO_x is contained within ± 10 ppmv and ± 2 kg/hr.

Emission factors in terms of Kg of NO_x per GJ of fuel burned are compared with values set forth by AP-42 of 0.127 kg/GJ (all loads), or 0.139 kg/GJ (for loads greater than 80%), and are shown in Fig. 8a. It indicates that for the most part, the actual NO_x emission factors are predominantly below AP-42 values. Comparison of the measured NO_x emissions with emission intensity guidelines for stationary combustion turbines published by CCME (Canadian Council of Ministers of the Environment) in 1992 [28] is shown in Fig. 8b. It clearly indicates that the LM1600 unit in question for the most part exceeds the emission intensity level according to 1992 CCME guidelines. It should be noted that this unit was installed well before 30 November 1994.

Uncertainty analysis was then conducted to assess the error on PEM predictions due to error in measuring any of the four engine parameters. Estimates of error in measuring the engine parameters are as follows:

1. Error in ambient temperature (T_{amb}) = ± 1 °C.
2. Error in engine speed (N1) = $\pm 1\%$
3. Error in compressor discharge pressure (P3) = $\pm 1\%$
4. Error in fuel flow (Qf) = $\pm 1\%$

The results of this uncertainty analysis are summarized in Table 3. It was shown that for uncertainty in the ambient temperature of ± 1 °C, the uncertainty in the NO_x prediction is ± 0.9 to $\pm 3.5\%$. Uncertainties of the order of $\pm 1\%$ in the other three input parameters result in uncertainties in NO_x predictions in the range of ± 2.5 to $\pm 6\%$.

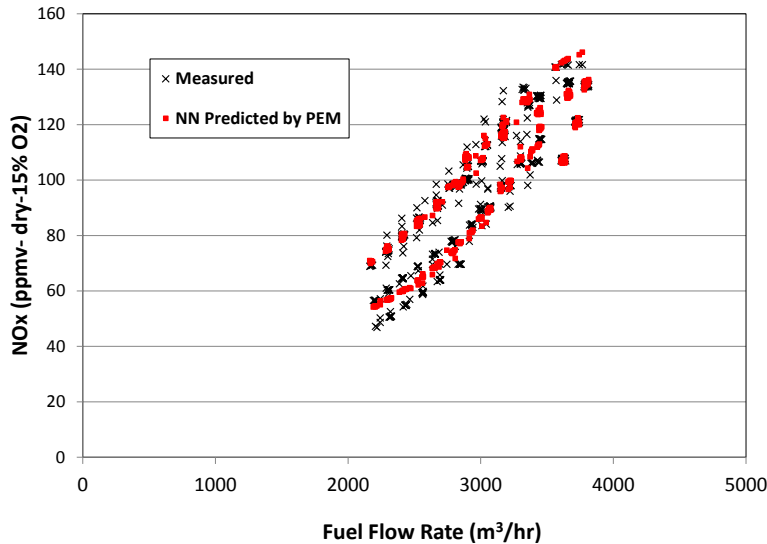


Figure 4: Comparison Between PEM Predicted vs. Measured and Cycle-Deck Data (in terms of ppmv-dry-15%O₂).

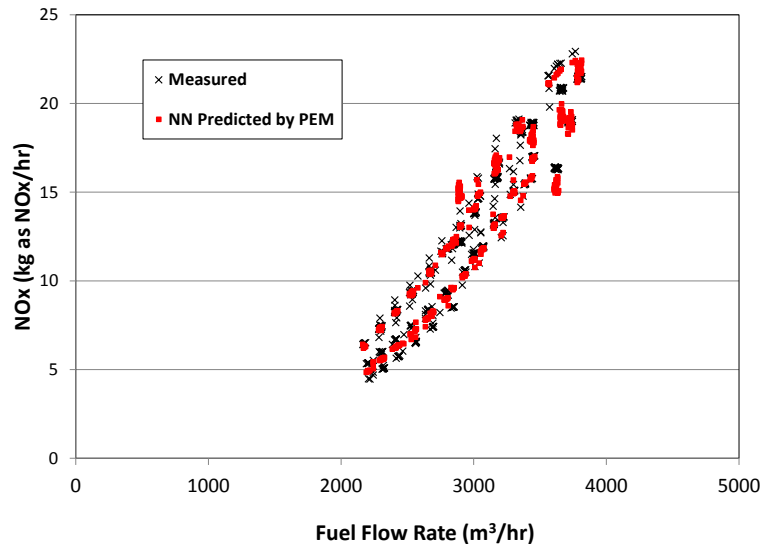


Figure 5: Comparison between PEM Predicted vs. Measured and Cycle-Deck Data (in terms of Kg/hr).

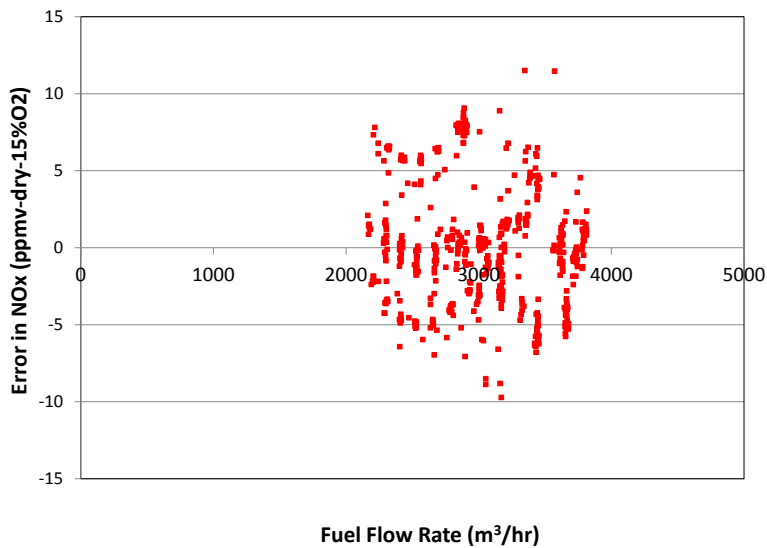


Figure 6: Error in PEM Prediction (in terms of ppmv-dry-15%O2).

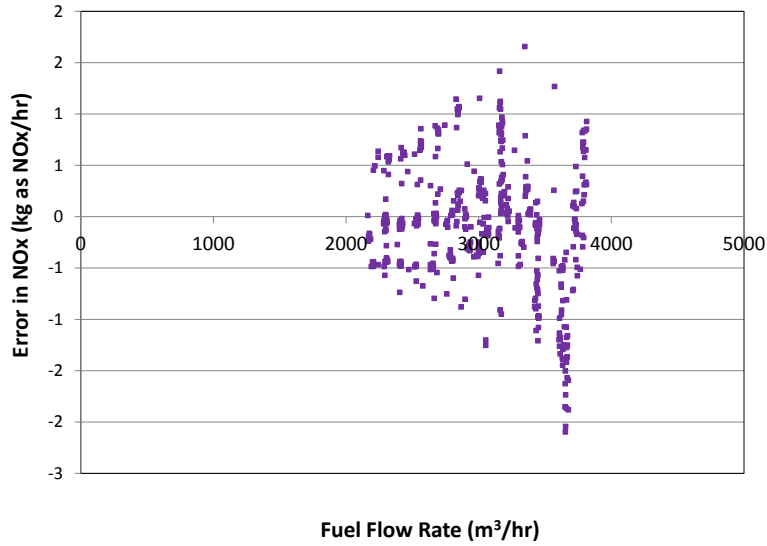


Figure 7: Error in PEM Prediction (in terms of Kg/hr).

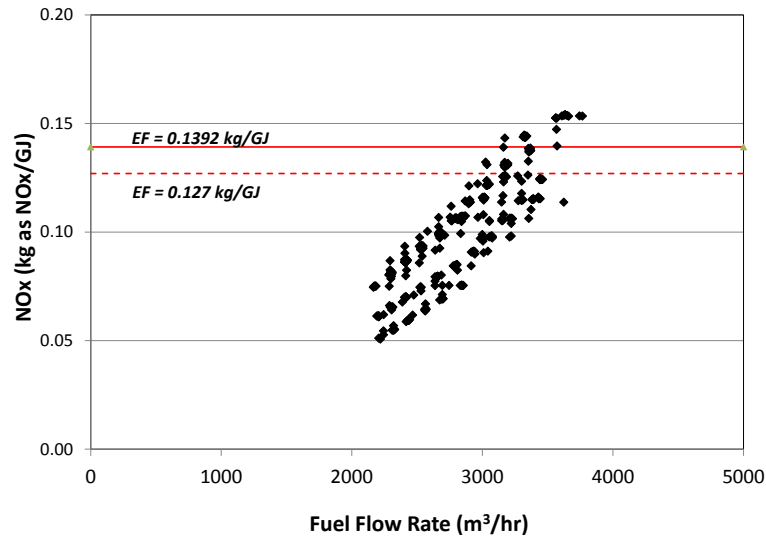


Figure 8a: Measured Emission Factor and Comparison with AP42 Emission Factors.

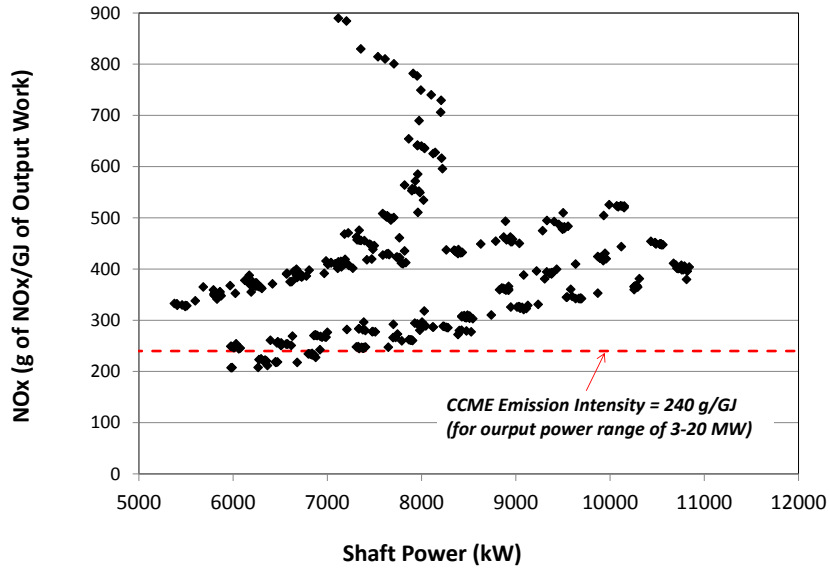


Figure 8b: Measured Emission Factor and Comparison with 1992 CCME Emission Intensity.

Table 3: Summary of the Uncertainty Analysis.

Uncertainty in	Level of Uncertainty (+ or -)	Error in NOx (ppmv + or - %)	Error in NOx (kg/hr %)
Ambient Air Temperature	1 deg C	0.90%	3.50%
GG Speed (N1)	1%	3.00%	6.00%
Compressore Discharge Pressure (P3)	1%	2.50%	5.30%
Fuel Consumption (Qf)	1%	2.80%	5.90%

6. Implementation

The above PEM model was implemented in two similar units employed in the station. The implementation was achieved via a module written in C++ and uploaded to the Compressor Equipment Health Monitoring (CEHM) system of the station. Figures 9 and 10 show collected data from the station CEHM system as a function of fuel flow rates.

Figure 11 shows hourly data over one year of emission inventory for both units (#6 and #7), in terms of Kg/GJ of fuel), based on predictions by present PEM model (Units 6 & 7). The two EF values of AP42 are also shown for comparison. It is shown that the predicted emission factors are below the higher AP42 EF value of 0.1392 kg of NO_x/GJ of fuel. This led to perform a calculation to determine the total emission inventory for the two units over this one year period using the present PEM model in terms of tonnes of NO_x emitted. A comparison is also made with the AP 42 EF values and the 80% load rule. The results are shown in Table 4, which indicates that Unit 6 actually emitted 20.99 tonnes of NO_x, while if the AP42 EF values and 80% load rule is applied, an estimate of NO_x emission would be 39.31 tonnes, which is nearly double the value predicted by PEM. Similar results are obtained for unit 7 as depicted in Table 4.

Finally, based on the measured data obtained for the RB211 [20], GE LM2500 [21], and that for the GE LM1600 engine reported here, comparisons are made between these three engines of the respective NO_x emission. These comparisons are shown in Fig. 12 (in terms of NO_x in ppmv-dry-15%O₂) and Fig. 13 (in terms of NO_x in kg/hr). It appears that GE LM2500 emissions are higher than the RB211 engines for the same fuel flow rate. NO_x emission from GE LM 1600 engine is slightly higher than GE LM2500 at the same range of fuel gas flow. This likely due the higher combustion temperature in the LM1600 engines than in the LM2500 (e.g. fuel flow rate of 3500 m³/hr, LM1600 would be close to full load, while LM 2500 would be at 50% load).

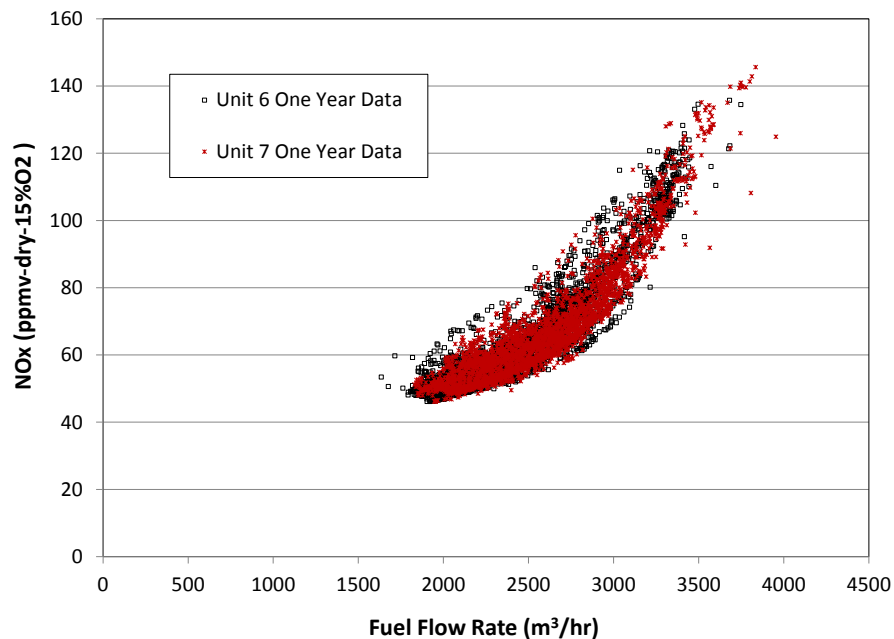


Figure 9: Estimate of One Year Emission Inventory (in terms of ppmv-dry-15%O₂) based on Predictions by Present PEM Model (Units 6 & 7).

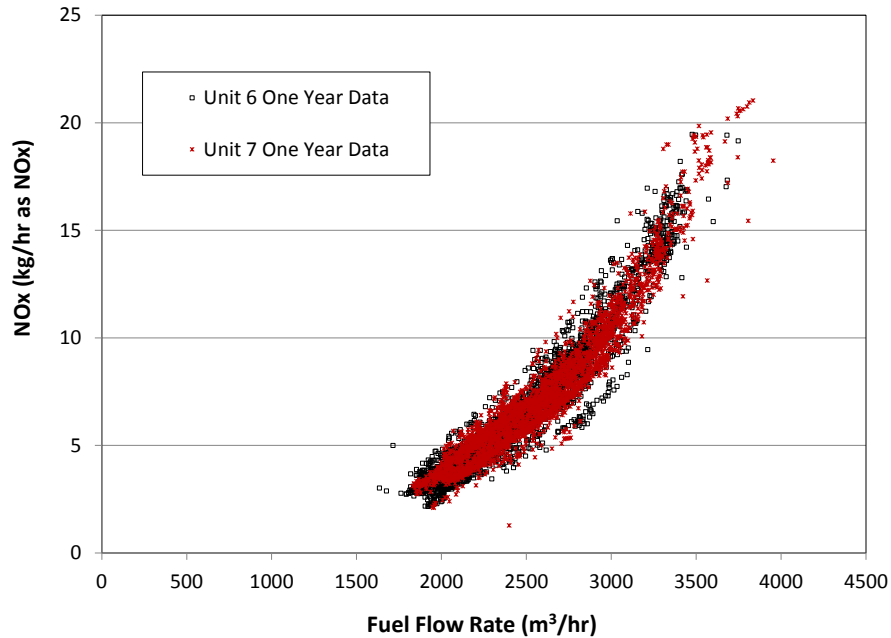


Figure 10: Estimate of One Year Emission Inventory (in terms of Kg/hr)based on Predictions by Present PEM Model (Units 6 & 7).

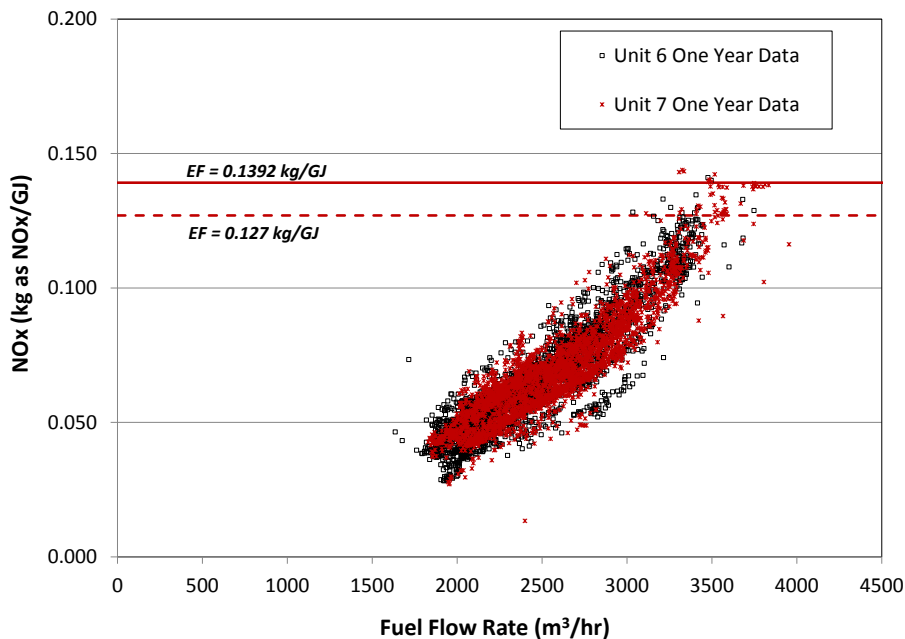


Figure 11: Hourly Data over One Year of Emission Inventory (in terms of Kg/GJ of fuel) based on Predictions by Present PEM Model (Units 6 & 7) and Comparison with AP42 Emission Factors.

Table 4: Comparison of NOx Emission Inventory from Units 6 and 7 over One Year Period, and Comparison with AP42 Emission Factors.

		Unit 6	Unit 7
Total Running Time in 1 Year	(hours)	3123	2911
PEM Predicted NOx Emission	(tonnes of NOx)	20.99	21.41
NOx Emission Based on AP42 Factors	(tonnes of NOx)	39.31	38.07

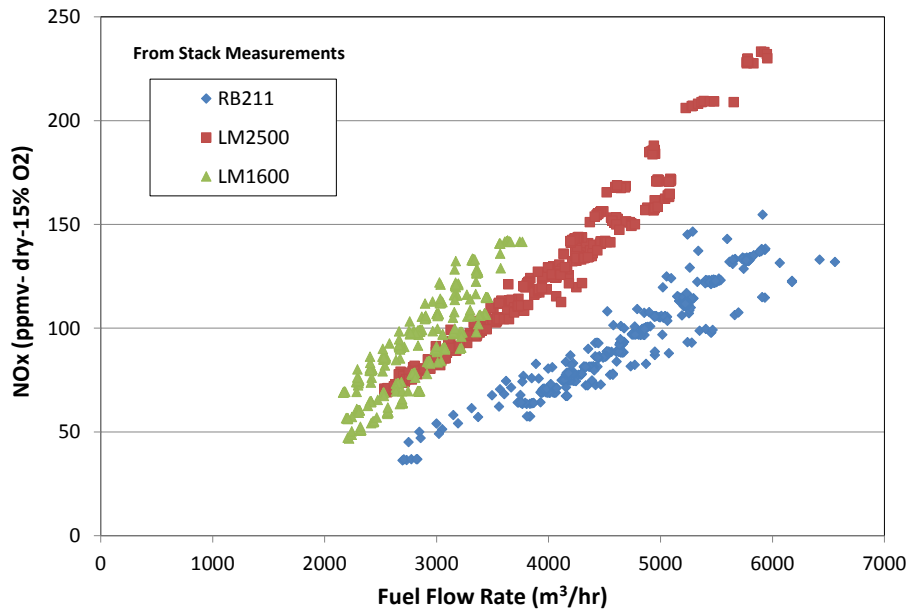


Figure 12: Comparison between Measured NOx Emission (in terms of ppmv-dry-15% O2) from three Different Gas Turbines Employed on Natural Gas Compressor Stations.

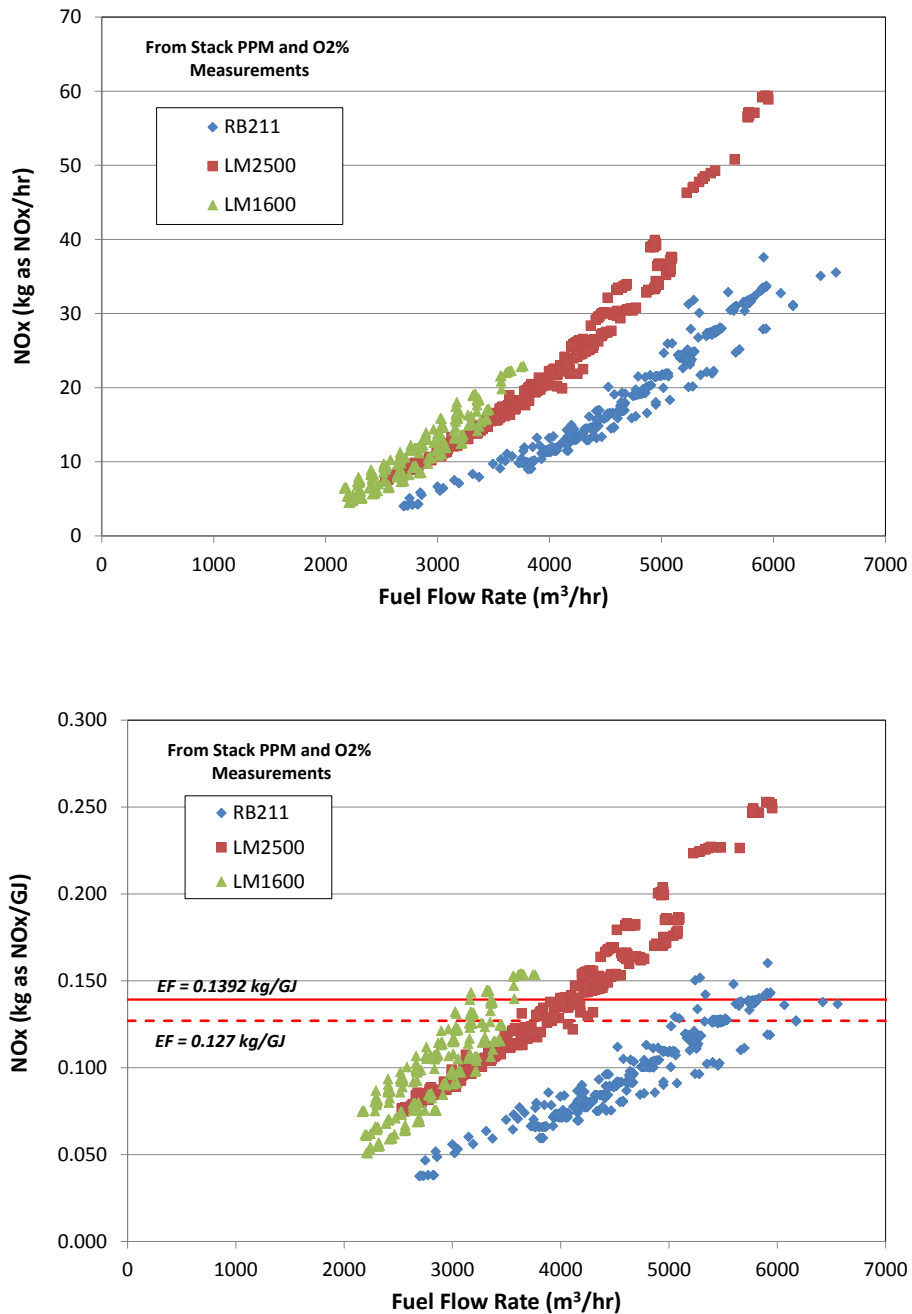


Figure 13: Comparison between Measured NOx Emission (in terms of kg/hr and kg/GJ) from three Different Gas Turbines Employed on Natural Gas Compressor Stations.

7. Concluding Remarks

The following five main conclusions can be drawn from the present investigation:

1. A simple Multi-Layer Perceptron type Neural Network with one hidden layer was found to be the optimum architecture for predicting NO_x levels with a standard deviation of the error on the order of ± 3.9 ppmv or ± 0.43 kg/hr.
2. It appears that actual NO_x emissions from the LM1600 engine at all loads are below the AP-42 full load value. It was pointed out that NO_x emissions inventory from a specific engine or a fleet of the same engine can be better quantified from a PEM model than from one or two values of EF provided by AP-42. This is because PEM models take into account engine parameters, particularly the fuel consumption (which is related to load), as well as ambient temperature in estimating the emission factors.
3. One year worth of emission inventory of two LM-1600 units employed in the same compressor station indicate that the actual emission inventories over this period is almost ½ of that predicted by the AP42 EF values and 80% load rule.
4. Finally, based on the measured data obtained for RB211, GE LM2500, and GE LM1600 engines, it was shown that GE LM2500 emissions are higher than the RB211 engines for the same fuel flow rate. These two engines are close to each other in terms of their ISO rated power. NO_x emission from GE LM-1600 engine is slightly higher than GE-LM2500 at the same range of fuel gas flow.
5. Close correlations between field test results and the PEMS predictions are demonstrated. This demonstrates that PEMs are viable alternative to CEMs, and produce more realistic results than using AP-42 factors.

8. Acknowledgments

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-1.0	12110.0	5943.2	1482.0	2430.6	54.8	5.7
-0.8	12113.6	5941.2	1473.0	2429.6	54.8	5.7
-0.9	12114.0	5953.3	1480.1	2429.6	54.8	5.7
-0.9	12112.2	5959.3	1481.0	2434.8	54.8	5.7
-1.0	12112.0	5943.2	1481.0	2443.1	55.1	5.8
-1.0	12115.0	6099.4	1480.0	2465.9	57.0	6.0
-0.9	12115.0	6113.5	1480.0	2562.5	58.7	6.5
-0.8	12204.3	6103.4	1541.0	2562.5	59.3	6.5
-0.7	12204.0	6101.4	1535.7	2568.7	59.5	6.6
-0.6	12204.0	6095.4	1535.0	2566.6	59.4	6.6
-0.6	12192.3	6095.4	1538.6	2557.3	59.3	6.5
-0.6	12192.8	6103.4	1539.9	2559.3	59.3	6.5
-0.6	12205.6	6103.4	1535.5	2568.7	59.3	6.5
-0.5	12207.0	6113.5	1540.4	2562.5	59.2	6.5
-0.5	12207.0	6103.4	1541.0	2565.6	59.8	6.6
-0.5	12286.9	6227.6	1541.0	2564.5	61.7	6.8
-0.5	12299.6	6235.6	1591.6	2672.5	63.4	7.3
-0.8	12300.0	6251.6	1592.8	2697.4	64.0	7.4
-0.7	12292.8	6259.6	1596.6	2697.4	64.0	7.4
-0.7	12292.0	6253.6	1597.0	2697.4	63.9	7.4
-0.8	12301.0	6237.6	1591.0	2689.1	63.8	7.4
-0.7	12291.0	6261.6	1600.1	2697.4	63.9	7.4
-0.6	12298.2	6247.6	1601.0	2693.2	64.0	7.4
-0.6	12299.0	6255.6	1598.0	2693.2	64.1	7.4
-0.5	12303.5	6237.6	1597.1	2693.2	65.7	7.6
-0.5	12304.0	6391.8	1597.0	2693.2	69.6	8.1
-0.5	12412.0	6383.8	1649.0	2745.1	69.6	8.2
-0.5	12429.1	6393.8	1663.4	2830.2	69.6	8.5
-0.6	12410.3	6389.8	1658.7	2852.0	69.6	8.5
-0.6	12408.0	6393.8	1658.0	2853.1	69.6	8.5
-0.5	12407.9	6399.8	1658.0	2841.6	69.6	8.5
-0.5	12400.8	6397.8	1653.0	2843.7	69.6	8.5
-0.6	12400.0	6403.8	1653.0	2843.7	69.6	8.5
-0.5	12405.6	6405.8	1663.0	2844.7	69.6	8.5
-0.5	12412.3	6393.8	1664.9	2840.6	69.7	8.5
-0.4	12529.2	6552.0	1710.4	3004.6	88.4	11.4
-0.3	12529.0	6554.0	1710.0	3004.6	89.1	11.5
-0.2	12529.9	6552.0	1710.0	3010.8	89.4	11.6
-0.1	12531.8	6540.0	1719.0	3004.6	89.4	11.5
-0.1	12532.0	6536.0	1720.0	3005.6	89.2	11.5
0.0	12532.0	6534.0	1714.0	2999.4	89.4	11.5
-0.1	12536.6	6548.0	1707.1	3005.6	89.4	11.5
0.0	12535.2	6554.0	1715.1	2983.8	89.6	11.5
0.0	12535.0	6544.0	1716.0	3003.5	89.7	11.6
0.0	12535.0	6558.0	1716.0	2995.2	89.8	11.6
-0.1	12535.0	6554.0	1719.6	2999.4	91.2	11.8
-0.1	12535.0	6622.1	1720.0	3054.4	96.7	12.7
-0.1	12535.0	6702.2	1720.0	3054.4	97.1	12.8
0.0	12660.4	6700.2	1769.3	3148.8	97.1	13.1
0.0	12658.3	6694.2	1771.6	3155.1	97.1	13.2
0.1	12658.0	6702.2	1772.0	3154.0	97.2	13.2
0.4	12658.0	6704.2	1772.0	3155.1	97.3	13.2
0.8	12673.6	6700.2	1774.5	3157.1	97.7	13.3
0.8	12675.0	6694.2	1775.0	3158.2	97.8	13.3
0.7	12674.1	6716.2	1773.2	3148.8	97.8	13.2
0.7	12674.0	6724.2	1771.2	3162.3	99.8	13.6
0.8	12755.5	6810.3	1771.0	3146.8	105.0	14.2
0.8	12787.4	6848.4	1837.1	3275.5	105.6	14.9
0.9	12782.8	6854.4	1824.7	3305.6	105.9	15.1
1.1	12782.0	6856.4	1831.1	3310.7	105.9	15.1
1.1	12790.1	6828.3	1832.0	3299.3	105.7	15.0
1.2	12795.5	6856.4	1830.3	3300.4	105.8	15.0
1.1	12796.0	6852.4	1837.8	3299.3	106.2	15.1
1.0	12784.6	6854.4	1839.0	3299.3	106.1	15.1
1.0	12797.1	6862.4	1838.6	3307.6	106.2	15.1
1.1	12799.0	6854.4	1839.0	3300.4	108.7	15.4
1.1	12879.8	6990.5	1881.6	3300.4	113.9	16.2
1.2	12893.0	6990.5	1888.0	3441.5	114.5	16.9
1.2	12893.0	6990.5	1888.0	3441.5	114.8	17.0
1.3	12906.2	7006.5	1892.4	3459.2	114.7	17.1
1.2	12910.0	7010.5	1891.0	3459.2	114.6	17.0
1.2	12910.0	7010.5	1891.0	3448.8	114.7	17.0
1.1	12902.8	6990.5	1889.2	3454.0	114.7	17.0
1.0	12902.0	6998.5	1895.3	3448.8	114.7	17.0
1.0	12902.0	7000.5	1896.0	3447.7	114.8	17.0
1.1	12904.6	6992.5	1886.6	3444.6	114.8	17.0
1.1	12911.2	6984.5	1901.9	3448.8	114.7	17.0
1.2	12912.0	7014.6	1904.0	3447.7	114.6	17.0
1.3	12912.0	6976.5	1904.0	3439.4	114.9	17.0

Appendix B NOx Data from GE Cycle Deck (GE-LM1600)

Data Point	Tamb (deg C)	N1 (RPM)	N3 (RPM)	CDP (kPa-a)	Qf (m3/hr)	Measured NOx (ppmv-dry-15% O2)	Measured NOx (kg/hr)
1	-30.0	12799.0	7350.0	1997.6	3623.9	107.4	16.3
2	-20.0	13060.0	7350.0	2003.4	3727.4	121.2	19.0
3	-10.0	13270.0	7350.0	2002.1	3796.3	134.1	21.5
4	0.0	13034.0	7350.0	1941.6	3662.0	135.1	20.8
5	10.0	12992.0	7350.0	1840.6	3439.5	130.0	18.8
6	20.0	12944.0	7350.0	1707.6	3167.2	118.7	15.8
7	30.0	12902.0	7350.0	1569.8	2897.2	100.2	12.2

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