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# INDUSTRIAL APPLICATION OF GAS TURBINES COMMITTEE

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## ARTIFICIAL NEURAL NETWORK-BASED PREDICTIVE EMISSION MONITORING SYSTEM FOR NOx EMISSIONS

**by**

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## ABSTRACT

Predictive Emission Monitoring (PEM) systems have been developed for four natural gas fired power generating facilities. The systems are based on an artificial neural network (ANN) using the power plant operation variables to predict the nitric oxide (NO) portion of the exhaust emissions. The PEM systems were trained with emission and operation data gathered from the facilities during normal operation. A multi-layer perceptron fully-connected feed forward network with two hidden layers was the best architecture for all of the facilities. Verification of the PEM systems involved querying the trained networks with independent data sets (i.e. Demonstration Periods). The accuracy of the system was determined using the relative accuracy (RA) calculations from the Environment Canada EPS 1/PG/7 report (Environment Canada, 1993) . The PEM system is an ideal system for the low emitting natural gas fired generating plants however the system could be adapted for other types of industries.

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*Key words:* Predictive emission monitoring system, artificial neural network, power generation, nitric oxide emission

## 1.0 INTRODUCTION

Predictive Emission Monitoring (PEM) systems have become fashionable in the past few years because of advances in computer processing capability and the concept of an artificial neural network. Artificial neural networks (ANN) are increasing in popularity because of their capability to examine highly complex non-linear problems, such as NOx formation. The use of neural networks has shown to be an effective alternative to the traditional statistical techniques (Schalkoff, 1992; Comrie, 1997). The PEM system methodology is intended to be used by facilities to meet compliance issues pertaining to measurement, monitoring and reporting requirements as an alternative to Continuous Emission Monitoring (CEM) systems.

The PEM-ANN system developed during this study predicts mass NOx (as NO) emission rates using readily available and measured physical variables associated with the combustion process (i.e. fuel consumption, power output, compressor discharge pressure, etc.). This was an important component of the design phase of the program; namely that we do not introduce additional measurement points. A general PEM system framework for the prediction of the nitric oxide (NO) portion of exhaust emissions from low mass emitting natural gas fired facilities is discussed.

The ANN system uses a multi-layer perceptron (MLP) model which consists of a system of simple interconnected neurons representing a non-linear mapping between an input vector (i.e. plant operational variables) and an output vector (i.e. NO emission rate). The neurons are connected by weights and output signals which are a function of the sum of the inputs to the neurons modified by a simple non-linear transfer or activation function.

The principle objective of this work was to develop an alternative monitoring method that is less expensive and as accurate as traditional CEM systems. Using the four gas turbine power plants operated, at the time of the system development, by TransCanada Energy Ltd.[1], a system was developed that achieved the required accuracy of the regulatory authorities. The results of the PEM systems are currently being reviewed by the Ministry of the Environment of Ontario (MOE). The following describes the PEM system architecture, facilities that were used in the development, approach to development and results.

Finding cost-effective ways to deal with changes in legislation impacting facilities already in operation is extremely important, especially considering the nature of long term power supply contracts that do not include mechanisms for cost recovery. It is also important to consider the age of the facilities, having not required CEM systems when put into operation but not yet old enough yet for capital stock turnover to allow for equipment changes or transition to new operations.

The advantages to having a regulator approved PEM system will no doubt be important to regulators and facilities alike as legislation is implemented requiring similar monitoring systems be in place at facilities in other sectors beyond electricity generation.

[1] These. facilities are now controlled by EPCOR.

## 2.0 SITE DESCRIPTION

The PEM system development program involved four power generating facilities operated, at the time of system development, by TransCanada Energy Ltd. - North Bay, Kapuskasing, Tunis and Nipigon. The facilities operate natural gas fired combustion gas turbines (CGT) in a combined cycle set-up with power generation between 22 – 31 megawatts (MW) of electricity production from the CGT units alone. Additional power is also produced by passing hot exhaust gases from the turbines, as well as adjacent compression facilities through a heat recovery steam generator (HRSG), making the facilities "enhanced combined cycle". The plants are base load plants with minimal start-ups and shutdowns. The facilities are all located in Northern Ontario, thus exposed to extreme climates on a regular basis. Table 1 summarizes the four facilities.

**Table 1 Summary of TransCanada Facilities**

| Facility | Turbine Output (MW) | Load | Gas turbine type | In-service date |
|---|---|---|---|---|
| North Bay | 25 | Base (22-31 MW) | FT-8 (DLN) | March 1997 |
| Kapuskasing | 25 | Base (20-30 MW) | FT-8 (DLN) | March 1997 |
| Tunis | 31 | Base (20-30 MW) | LM6000 | January 1995 |
| Nipigon | 22 | Base (19-23 MW) | LM2500 | May 1992 |

North Bay and Kapuskasing facilities have dry low NOx (DLN) control systems to reduce the NOx emissions. The DLN system is used to control local fuel/air ratio and fuel zones for optimum low emissions and combustion stability. As well, these two facilities have duct burners to heat the gas turbine exhaust gases entering the HRSG to increase the power output of the steam generator. The other two facilities do not have any type of NOx controls.

## 3.0 NITROGEN OXIDE (NOX) CHEMISTRY

Products of combustion include carbon monoxide, carbon soot, aldehydes and nitrogen oxides. The major component of nitrogen oxides ($NO_x$) is nitric oxide (NO) which is formed due to the high temperatures in the post flame area, known as thermal NOx. NO may react to form $NO_2$, $N_2O$, $N_2O_3$ or $N_2O_5$ later either when temperatures are cooler in the stack or after being exhausted. Other processes contribute to the total $NO_x$ emissions: reactions within the flame area with cyanide compounds – termed prompt $NO_x$; and the nitrous oxide process that involves the reaction of O with $N_2$ to form $N_2O$ which oxidizes to NO; and another process of formation is from the nitrogen contained in the fuel which produces $NO_2$ (Botros et al, 2001).

## 4.0 SUPPORT FOR USE OF PEM SYSTEM

The facilities used in the study are part of the many small power generating stations located across Canada which operate with very few full time employees and under well-defined load conditions. A PEM system is an ideal solution to providing accurate and environmentally sound emission predictions as the results here show. The US EPA and Environment Canada have indicated that these facilities may be better served using a PEM system instead of a CEM system. The US EPA has recently released its own set of criteria for the development of PEM systems. The protocol and analysis used in this PEM system development would be sufficient to meet the intent of the US requirements as currently proposed (USEPA, 2005) and would therefore also make a good template to develop a Canadian guideline for PEM systems. As well, there is a lower capital investment with a PEM system than a CEM system. Existing facilities without an installed CEM system can face extremely high retrofit costs when compared with installation of a CEM system at the time of construction of a new facility.

The decreased costs are also due to the shared nature of a PEM system, utilizing equipment and information otherwise necessary for the operation of a facility. This leads to an added potential benefit of being able to correlate operation of a facility directly to emissions levels. CEM systems don't often share this capability and therefore don't offer the same potential opportunity to "fine tune" operations to reduce emissions even lower than the currently low levels from natural gas facilities.

## 5.0 REGULATORY CONTEXT

PEM systems can be designed to achieve results for the various reporting regulations. Currently the NO portion has been predicted, however the system has the ability to predict the mass emission rate of nitrogen oxides in whatever metric regulatory authorities require. At the commencement of this study O.Reg. 397/01 required only the NO portion to be reported, however, the regulation has been recently amended to O.Reg. 193/05 which requires total nitrogen oxide expressed as nitrogen dioxide (i.e. the sum of NO converted to $NO_2$, and $NO_2$).

Development of the new system will only require the change of emission data to the proper reporting metric. Operation data of the sampling period can be reused to redesign the system.

The other requirement of Regulation 397/01 was that any PEM system must have the ability to meet the federal Canada guideline for CEM systems (EPS 1/PG/7), as previously discussed. This became the general "test" for the study outlined herein.

## 6.0 WHAT IS AN ARTIFICIAL NEURAL NETWORK (ANN)?

Artificial neural networks are data analysis methods and algorithms based loosely on the nervous systems of humans and animals. The human brain is orders of magnitude more complex than the ANN. An ANN in general terms is a network consisting of a large number of simple processing units linked by weighted connections. The main processing unit of the network is the neuron and the power of the network comes from the combination and connections between the neurons. The ANN can be adjusted to the particular problem by tuning the parameters of the neural network such as input variables, algorithms, method of architecture search, weights of the variables and many more. The more complex the problem, there is a greater variation of the parameters used in the creation of a network.

A multi-layer perceptron (MLP) is the most common form of a neural network. The MLP consists of a system of neurons which represents a non-linear mapping between the inputs and outputs. The neurons are connected by weights and output signals that are the function of the sum of the inputs modified by a simple non-linear transfer or activation function. It is the activation function involved in all of the connections which make it possible for the neural network to approximate extremely non-linear functions. The logistic function is the most commonly used function (Figure 1). The logistic function has a sigmoid curve and is calculated using the following formula: $F(x) = 1/(1+e^{-x})$. Its output range is [0...1]. The output produced by a neuron is fed forward to be an input for neurons in the next layer. This information flow is referred to as a feed forward process.

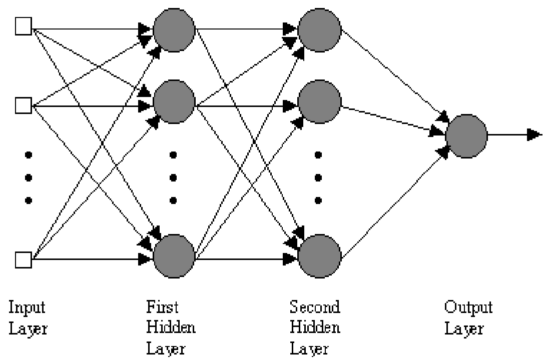



**Figure 1 A multi-layer perceptron feed-forward artificial neural network generalized architecture (Source: http://www.nd.com).**

The architecture of a MLP varies depending on the problem; however the MLP tends to have multiple layers of neurons. The input layer only passes the input variables into the network, no calculations occur in this layer. A MLP is fully connected, with every neuron connected to neurons in the previous and next layers. According to Hornik et al. (1989), if the appropriate weights and activation function are chosen then the MLP can approximate any smooth, measurable function between inputs and outputs.

## 7.0 ANN PROCESS – ANALYSIS/PRE-PROCESSING/DESIGN/TRAINING/QUERYING

Preparation of data sets is critical when working with an artificial neural network (ANN). The ANN requires certain qualities with input data, for example, proper quantity of data, data should not be self-contradictory, inputs should have maximum influence on output, no missing values or outliers, and data should represent the problem. The quality of the input data plays a large role in the creation of an accurate neural network.

The ANN development process begins with organizing the data into paired data sets and being confident the data meets the required quality for input into the software. Analysis of the data includes a search for missing values and outliers, subdividing data into training, validation and test data sets and pre-processing.

Training period data is subdivided into the three sets for the training process. The training set is the input data used to train the neural network – data is used to adjust network weights to maximize the accuracy of the predictions and reduce the amount of error. The validation set is used to tune the network topology or network parameters other than weights. The test set is used only to estimate the quality of the training of the neural network and is the portion of the training data that is not presented to the network for training.

Pre-processing involves the transformation of data before being fed into the neural network. The data is scaled into a numerical format which is required for data to be processed. Following pre-processing the next step is to design architecture to be used by the network. The architecture design stage involves using the input training data and various search parameters to specify the number of layers in the neural network and the number of neurons per layer along with activation functions for layers and network error function. Determining the best architecture is an essential step to being able to solve the problem.

Training the neural network is the next step and the purpose of training is to teach the network to associate specific output values with a given set of input-output data. During training, input data is presented to the network and signals are propagated forward through the network. The response produced in the output layer is then compared to the desired response. Training will continue to change the weights between network units (neurons) to reflect dependencies in the data. Following training the network is ready to be queried with new unseen data (i.e. Demonstration periods) to test the generalisation of the network. Generalisation refers to the ability of the network to respond to inputs it has not encountered during the training process. The ability to generalize is essential to the decision making ability and accuracy of the network.

A trial and error method using the above ANN process was used to determine the best networks for the four sites. The method involved changing the fitness criterion, increasing the search range, reducing the search step or accuracy, increasing the number of retrains per configuration, increasing number of iterations per configuration, changing algorithms, combinations of operational variables and changing other network training parameters.

## 8.0 DATA COLLECTION PROGRAM

Emission and plant operation data were collected from the four facilities to obtain a sufficiently sized dataset of NO, $NO_2$, $NO_x$ and $O_2$ measurements and plant operational data to be used to develop the PEM system. The NO data was used for this particular study. The paired data was collected on a minute by minute basis with emission data reported in ppm and oxygen data in percent. Plant operational data was reported in the appropriate units for each variable. Data collection was carried out during normal operation of the facility.

The data collection program comprised of a Training Period and two Demonstration Periods (Table 2). Training periods consisted of approximately 32 – 36 hours of data, and Demonstration periods consisted of approximately 72 hours. A separation period of a minimum of 48 hours was scheduled between the two demonstration periods. The training period data was used to train and prepare the PEM system following the method described previously. Verification of the system involved the use of the Demonstration Periods to show independently of the training data set that the PEM system could accurately predict emissions.

## Table 2 Schedule of Testing

| Site | Phase | Period | Start Date/Time | Finish Date/Time | Full scale (ppm) | Load | Gas turbine status | Gas Turbine |
|---|---|---|---|---|---|---|---|---|
| North Bay | Fall | Training | 10/25/04 4:18 | 10/26/04 11:59 | 50 | | Normal operation | FT-8 (DLN) |
| | | Demonstration #1 | 10/26/04 13:00 | 10/29/04 13:00 | 50 | Low/High | Normal operation | |
| | | Demonstration #2 | 11/1/04 4:30 | 11/4/04 7:59 | 50 | Low/High | Normal operation | |
| | Winter | Training | 1/24/05 3:00 | 1/25/05 16:00 | 50 | | Normal operation | FT-8 (DLN) |
| | | Demonstration #1 | 1/25/05 17:00 | 1/28/05 18:12 | 50 | Low/High | Turbine Malfunction | |
| | | Demonstration #2 | 1/31/05 16:00 | 2/3/05 19:23 | 50 | Low/High | Lease turbine installed | |
| Kapuskasing | Winter | Training | 2/14/05 4:30 | 2/15/05 23:59 | 50 | | Normal operation | FT-8 (DLN) |
| | | Demonstration #1 | 2/16/05 0:00 | 2/18/05 23:59 | 50 | Low/High | Normal operation | |
| | | Demonstration #2 | 2/21/05 4:00 | 2/24/05 19:00 | 50 | Low/High | Normal operation | |
| Tunis | Winter | Training | 6/2/05 19:00 | 8/2/05 20:00 | 250 | | Normal operation | LM6000 |
| | | Demonstration #1 | 8/2/05 20:01 | 12/2/05 12:55 | 250 | Low/High | Normal operation | |
| | | Demonstration #2 | 3/23/05 16:00 | 3/27/05 8:15 | 250 | Low/High | Normal operation | |
| Nipigon | Winter | Training | 3/11/05 17:16 | 3/13/05 7:00 | 250 | | Normal operation | LM2500 |
| | | Demonstration #1 | 3/13/05 19:01 | 3/16/05 22:00 | 250 | Low/High | Normal operation | |
| | | Demonstration #2 | 3/16/05 22:01 | 3/22/05 8:00 | 250 | Low/High | Normal operation | |

**NOTES:**

1. Span, downloading, sampling and operational down periods were removed from the training and demonstration period data before ANN training and querying.

2. Relative accuracy (RA) calculations were based on EPS 1/PG/7 methodology. As the NO concentration at all sites was below 250 ppm, the Full Scale value was substituted for the Reference Method average in the RA equation. Relative accuracy was calculated based on a mass per time basis (g/s).

## 9.0 PLANT OPERATION VARIABLES

Plant operational variables required for the PEM system were collected from plant data collection systems (DCS). These variables are part of the CGT train and are used to routinely monitor behaviour and performance of the CGT. The sensors provide measurements once per minute. The CGT is a precision machine and has many variables that must function in sync to realize an optimum output.

Operational variables were chosen based on the availability and current set-up of the DCS. A trial and error process was used to determine the best combination of variables for accurately predicting emissions and as a result not all of the variables collected were used in the final PEM system.

The PEM systems of the four facilities used some of the same operational variables. For example, the North Bay and Kapuskasing facilities used the same six operational variables whereas Tunis and Nipigon used thirteen and seven variables respectfully. Table 3 provides a summary of the plant operational variables for all of the facilities. An interesting note is that the North Bay and Kapuskasing used the same variables and further testing is being conducted to develop an interchangeable ANN for facilities using similar types of gas turbines.

**Table 3 Operational variables from the four facilities**

| North Bay [FT-8 (DLN)] | Kapuskasing [FT-8 (DLN)] | Tunis [LM6000] | Nipigon [LM2500] |
|---|---|---|---|
| GT fuel gas | GT fuel gas | GT fuel gas | GT fuel gas |
| Compressor outlet temperature | Compressor outlet temperature | HPC discharge temperature - compressor discharge temperature | CDP temperature |
| CDP pressure | CDP pressure | HPC discharge st. pressure - compressor discharge pressure | Power turbine inlet temperature |
| Mass flow | Mass flow | Mass flow | Ambient temperature (compressor inlet temperature) |
| Power | Power | Power | HRSG #1 inlet temperature |
| Ductburner fuel gas | Ductburner fuel gas | LPT inlet temperature - turbine inlet temperature | HRSG #1 exhaust temperature |
| | | Ambient temperature | LM2500 RPM |
| | | Combustor exhaust avg. temp - turbine exhaust temperature | |
| | | Stack exhaust | |
| | | LPT inlet total pressure - turbine inlet pressure | |
| | | HPC total air pressure - compressor inlet pressure | |
| | | HPC inlet air temperature - compressor inlet temperature | |
| | | LPC inlet temperature - compressor inlet temperature | |

## 10.0 DATA PROCESSING

Emission data was processed before the development of a neural network. Processing involved converting the concentration emission data to a mass emission rate and pairing the emissions with the plant operational data. Periods of interruptions in the data, for example, periods of data downloading, span checks, sampling and operation down periods were removed from the data used to train and verify the PEM system.

NO mass emission rates were calculated using F-factors – Method A (Environment Canada Report EPS 1/PG/7, Sept. 1993, Appendix B – Determination of Mass Emission Rates) from the source testing data and fuel consumption.

Equation 1 transforms the NO concentration from a volume basis to a mass per time (g/s) basis.

$$\text{ERx} = HI \cdot C_{d,x} \cdot F_d \cdot K_x \left[ \frac{20.9}{20.9 - \%O_{2d}} \right] \qquad \textbf{(1)}$$

Where:

$ER_x$ = emission rate of pollutant (g/s)
HI = gross heat input (MJ/hr)
$C_{d,x}$ = dry-basis concentration of NO (ppm)
$F_d$ = ratio of the volume of dry gas resulting from stoichiometric combustion of the fuel with air, to the amount of heat produced (Natural gas = 0.247 dscm/MMJ )
$K_x$ = conversion factor for ppm into ng/scm (1.23 x $10^6$ ng/scm for NO)
$\%O_{2d}$ = dry-basis concentration of oxygen (%, dry, v/v )

## 11.0 PEM SYSTEM

Equation 2 below is the simplified NO function for the Tunis facility PEM system.

$$NO_{EG} = NO_{GT} = fn(Q_T, MW, T_{EX}, P_{2C}, T_{2C}, Fl, T_{in}, AT, HT, HP, HCDT, HDP, T_{stack}) \qquad \textbf{(2)}$$

Where:

$NO_{EG}$ = NO emissions from electrical generation (g/s)
$NO_{GT}$ = Emissions of NO after Gas Turbine (g/s)
fn() = Artificial neural network function

The trained PEM system is designed to react to the changes/fluctuations in the operation variables. This was achieved during training when the weights of the each variable were determined. Each facility has a unique system designed specifically for the unit that was in operation at the time of the study. The architectures of the facilities are in Table 4.

**Table 4 Architectures for the four facilities**

| Facility | ANN Architecture |
|---|---|
| North Bay | 6-14-9-1 |
| Kapuskasing | 6-14-4-1 |
| Tunis | 13-24-11-1 |
| Nipigon | 7-16-9-1 |

The ANN based PEM system will be composed of the trained neural networks model and a stand alone computer. The appropriate plant variables will be downloaded from the plant data collection systems and fed through the PEM system. Minute by minute and hourly averages of emissions will be determined and stored on the data collection system. Emissions will be continuously predicted while the plant is in operation. Process interruptions or an equipment change will require the system to be retrained.

Tuning (re-training) may be performed to enhance the accuracy of the PEM system for the following reasons: process aging, significant process modification, and new process operating modes. The PEM system must be tuned on an augmented set of data which includes the set of data used for developing the system in use prior to tuning and the newly collected set of data needed to tune the system. Verification that the PEM system is acceptable after tuning will be performed utilizing a set of the recent paired data set of reference test method emissions data and plant operational variables.

## 12.0 RESULTS

Through a trial and error research process a feed-forward fully connected multi-layer perceptron neural network with two hidden layers was found to be the best ANN for predicting NO emissions at the four facilities. The trial and error process involved evaluating all of the functions, data, parameters and algorithms and determining the best combination. These network parameters were similar between the facilities, with only the architecture varying from facility to facility.

Each PEM system used the same activation function (logistic), error function (sum-of-squares) and training algorithm (conjugate gradient descent (CGD)). CGD was chosen as it is a general purpose training algorithm and was recommended when working with large sets of data. CGD has nearly the convergence speed of second-order methods, while avoiding the need to compute and store the Hessian matrix. Its memory requirements are proportional to the number of weights. Through a trial and error process the CGD algorithm was discovered to provide the best results when training the PEM systems. Originally, the back propagation algorithm was chosen as it was one of the more popular algorithms to train multi-layer perceptron networks. However the algorithms main drawbacks of slow convergence need to tune up the learning rate and momentum parameters, and high probability of getting caught in local minima created more difficulty to use then CGD. The convergence to a good solution was more probable with the CGD algorithm. CGD is a method what works faster than back propagation and provides more precise forecasting results.

Each facility has a unique PEM system based on the CGT unit and existing operational set-up. Ranges of the operational variables vary with each site. The quantity of data points varied from facility to facility due to the removal of data points and length of time sampling occurred. The PEM systems were developed using data collected during a period of normal operation.

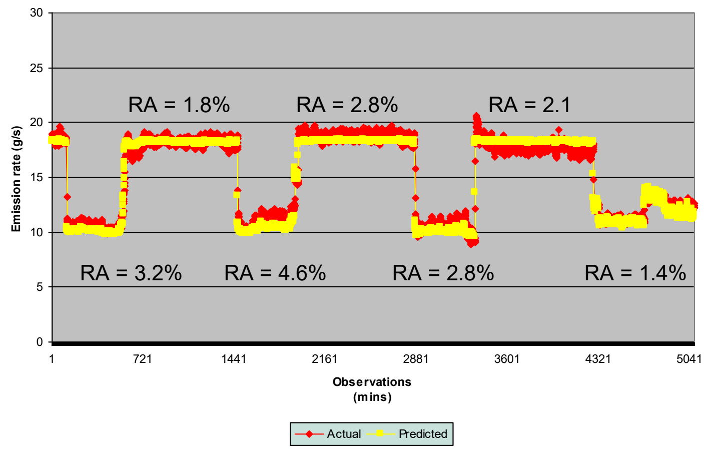
Minimization of the error and developing an accurate prediction system were the main objectives of the neural network training. Through the trial and error process systems were developed based on achieving the two objectives. Verification of the systems was completed to determine the predictability or accuracy. The verification process involved feeding unseen data (i.e. Demonstration Period) into the trained networks and comparing the predicted output value with the actual (measured) value. The accuracy of the PEM system was determined using the relative accuracy (RA) calculations as per EPS 1/PG/7 report. The average RAs for the four sites are in Table 5. These values were calculated using the full-scale of the analyzer converted to a mass emission. Based on the results the PEM systems meet the requirements of the guideline and would not require semi-annual testing of the PEM system. Graphical results for the Tunis facility are shown in Figure 2.

A variety of statistical metrics were calculated to determine the accuracy of the PEMS (Table 5) including relative accuracy, which is a comparative evaluation of the PEM system performance compared to a reference method (RM) (measured values). An acceptable RA value is less than 10%.

**Table 5 Accuracy statistics of the PEM systems**

| Site | Phase | Period | Load | Emission | Mean | Variance | Std Deviation | Average RA values |
|---|---|---|---|---|---|---|---|---|
| North Bay | Fall | Demonstration #1 | High | Actual | 1.70 | 0.011 | 0.104 | 2.6 |
| | | | | Predicted | 1.70 | 0.004 | 0.066 | |
| | | | Low | Actual | 0.96 | 0.003 | 0.056 | |
| | | | | Predicted | 0.87 | 0.005 | 0.069 | |
| | | Demonstration #2 | High | Actual | 1.80 | 0.005 | 0.071 | 4.7 |
| | | | | Predicted | 1.71 | 0.001 | 0.031 | |
| | | | Low | Actual | 1.10 | 0.013 | 0.115 | |
| | | | | Predicted | 0.89 | 0.034 | 0.185 | |
| | Winter | Demonstration #1 | High | Actual | 1.59 | 0.437 | 0.661 | 9.1 |
| | | | | Predicted | 2.18 | 0.159 | 0.398 | |
| | | | Low | Actual | 0.98 | 0.042 | 0.204 | |
| | | | | Predicted | 1.10 | 0.031 | 0.177 | |
| | | Demonstration #2 | High | Actual | 1.17 | 0.533 | 0.730 | 14.8 |
| | | | | Predicted | 2.18 | 0.208 | 0.456 | |
| | | | Low | Actual | 0.75 | 0.007 | 0.082 | |
| | | | | Predicted | 0.88 | 0.021 | 0.145 | |
| Kapuskasing | Winter | Demonstration #1 | High | Actual | 1.99 | 0.012 | 0.111 | 3.1 |
| | | | | Predicted | 1.85 | 0.038 | 0.194 | |
| | | | Low | Actual | 1.07 | 0.007 | 0.082 | |
| | | | | Predicted | 1.07 | 0.010 | 0.098 | |
| | | Demonstration #2 | High | Actual | 1.91 | 0.020 | 0.141 | 2.7 |
| | | | | Predicted | 1.86 | 0.069 | 0.263 | |
| | | | Low | Actual | 1.04 | 0.006 | 0.074 | |
| | | | | Predicted | 1.08 | 0.007 | 0.083 | |
| Tunis | Winter | Demonstration #1 | High | Actual | 18.23 | 0.373 | 0.611 | 2.7 |
| | | | | Predicted | 18.24 | 0.009 | 0.097 | |
| | | | Low | Actual | 11.22 | 0.821 | 0.906 | |
| | | | | Predicted | 10.69 | 0.895 | 0.946 | |
| | | Demonstration #2 | High | Actual | 17.67 | 0.701 | 0.838 | 2.7 |
| | | | | Predicted | 18.23 | 0.081 | 0.284 | |
| | | | Low | Actual | 13.06 | 1.955 | 1.398 | |
| | | | | Predicted | 12.19 | 1.085 | 1.042 | |
| Nipigon | Winter | Demonstration #1 | N/A | Actual | 9.89 | 0.521 | 0.722 | 3.8 |
| | | | | Predicted | 9.89 | 0.269 | 0.518 | |
| | | Demonstration #2 | N/A | Actual | 9.86 | 0.418 | 0.647 | 2.6 |
| | | | | Predicted | 10.07 | 0.469 | 0.685 | |

**Figure 2 Tunis Demonstration Period #1 – NO actual and predicted emissions**




## 13.0 CONCLUSIONS

The PEM system provides a cost effective method to monitor emissions accurately and reliably at low emitting natural gas fired facilities. As well, there is a great potential for the system to be used by other industries to monitor and report emissions.

The practical benefits of a PEM system that can accurately predict process emissions are great.

1. Costs

   a. Capital investment – PEM system low compared to CEM system.

   b. Cost effective – Installation and maintenance cost of a PEM system lower compared to a CEM system.

   c. Labour – Less time required for system maintenance allowing employees to focus on other tasks as well as reducing overall system downtime and therefore non-compliance events related to such downtime.

   d. Supplies and parts – PEM system does not require the purchase of gases and/or additional supplies, once again decreasing the costs and potential downtime/non-compliance events.

2. Ability to detect anomalies in the power generation operational system as well as to better understand correlations between operating conditions and emissions levels. This would allow "fine-tuning" of operations to maximize power output while maintaining emissions compliance or potentially reducing emissions.

3. Hands off – Once running the system does not require any additional input (i.e. gas cylinders do not have to be changed).

4. PEM system adaptable to the specific set-up of a facility. No additional set-up (i.e. wiring, gases) are necessary. This allows for easy retrofit to existing facilities, minimizing downtime and increasing the ability of a facility to come into compliance with newly implemented emissions monitoring and reporting legislation.

These benefits should be taken into account by companies and regulators alike when considering options for compliance with growing regulatory requirements for emissions monitoring and reporting. Barriers, such as the lack of applicable criteria, should be removed in order to allow for PEM systems to be implemented as an effective and accurate emissions monitoring system. As barriers are removed and society becomes familiar with the use of PEM systems, one can imagine that emissions monitoring issues will decrease over time.

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