Journal of Advanced Science and Engineering Research Vol 4, No 1 March (2014) 37-46

Prediction Of Nox Using Support Vector Machine For Gas Turbine Emission At Putrajaya Power Station

Article Info

Received: 5/1/2014
Accepted: 28/1/ 2014
Published online: 1/3/2014

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SSN 2231-8844

Abstract

The monitoring of flue gas emission from power generation is mandatory in Malaysia where the conventional way of measuring the emission is using field instrumentation (in-situ or extraction type) commonly known as Continuous Monitoring Emission System (CEMS). This system requires high maintenance cost on the instrumentation, spare parts/kits and calibration gases. The purpose of this research is to study an alternative way of measuring the emission gases by using artificial intelligence prediction method called support vector machine (SVM). The research concentrated on predicting NOx, the flue gasses emitted by power generation plant. The data have been collected from gas turbine parameters critically related with gas turbine combustion and NOx reading from CEMS. The data was run for supervised learning and creating a model to predict NOx emission. The prediction models used for this study were radial basis function and polynomial. The predicted results were compared with the reading from the CEMS and the percentage average of accuracy recorded was 98.14% for radial basis function model and 96.95% using polynomial model. The result shows that the prediction method to predict NOx is reliable and accurate. The complete implementation of this software enable the power generation to lower the maintenance cost since the maintenance of this system is only on the server/PC maintenance and yearly relative accuracy test audit (RATA) which is very minimum compare to CEMS maintenance on the field instruments, parts/kits and calibration gasses.

***Keyword*:** Gas Emission Prediction, NOx, Support Vector Machine (SVM), Continuous Emission Monitoring System (CEMS)

1. Introduction

Monitoring of flue gas emission in power generation is compulsory as regulated by the Department of Environment (DoE), Malaysia. TNB power generation in Malaysia uses Continuous Emission Monitoring System (CEMS) to measure the emission produce either by gas turbines (open cycle or combined-cycle), conventional boilers or coal fired boilers. The CEMS measure the flue gas emission continuously and instantaneously for operational monitoring purposes and reporting to DoE. The measurement using CEMS is operationally expensive to maintain and the reliability of the reading sensitive to the surrounding conditions (Chien, Chu, Hsu, Tseng, Hsu, & Chen, 2003).

Prediction of the flue gas emission or normally known as Predictive Emission Monitoring System (PEMS) was first introduce in 1992 and approved by United States Environmental Protection Energy (EPA) as the alternative means to CEMS (Swanson & Lawrence, 2009). The first patented PEMS used the nonlinear hybrid modeling methodology (Rockwell Automation, 2009). Since then, a lot of studies on the prediction of emission using several other method such as statistical hybrid (Chien, Chu, Hsu, Tseng, Hsu, & Chen, 2003), artificial neural network (ANN) (Zhou, Cen, & Fan, 2001) and combination of hybrid genetic algorithm and linear regression (GA-LR) (Bunyamin, Yap, Abdul Aziz, Tiong, Wong, & Kamal, 2013).

The latest development of predicting the emission from power generation is by using support vector regression (Zheng, Jia, Yu, & Yu, 2010). In machine learning, support vector machine (SVM) provides good prediction especially for nonlinear classification by using kernel trick by applying maximum-margin hyperplanes (Cortes & Vapnik, 1995). The resulting algorithm is replaced by a nonlinear kernel function. Some common kernels include Polynomial (homogeneous or inhomogeneous), Gaussian radial basis function and hyperbolic tangent.

This research is about a study to create the model for prediction of NOx emission from gas turbines due to high capital, operational and maintenance cost of the existing system called Continuous Emission Monitoring System (CEMS) (Chien, Chu, Hsu, Tseng, Hsu, & Chen, 2003). The predicted NOx using SVM was compared to the existing CEMS readings for the best percentage of average accuracy.

Nowadays, cost effectiveness plays major role in power plant projects and operation. The high capital cost of installing CEMS equipment may affect power plant competitive bidding chances. Besides that, operation and maintenance of the CEMS is expensive considering the calibration requirements, calibration gas cost and parts replacement cost. By utilizing the existing gas turbine measurements, the emission can be predicted only by having a server (computer) that are connected to the distributed control system and a prediction software. The capital cost, operational and maintenance cost is very much cheaper and this method has is accepted in United States by the Environment Protection Agency (EPA).

2. Literature Review

2.1 Predictive Emission Monitoring System

Chien et al., 2003 defines concept of Predictive Emission Monitoring System (PEMS) as using the concept of thermodynamics or statistical method in order to construct a mathematical model that can predict the flue gas emission from the gas turbines. They established the research using computer program known as statistical software (SAS). The major variables to determine NOx and O2 were obtained based on knowledge on combustion theory. Based on knowledge of thermodynamics and combustion theory, the independent variables selected were combustion temperature (T), air to fuel ration (φ) and combustion pressure (P). The constant coefficients were obtained through the SAS software. Predictive emission monitoring system was considered as a solution to the expensive capital cost of Continuous Emission Monitoring System (CEMS) as well as an alternative for cheaper method in term of operational cost. Besides that, the CEMS has the disadvantages of producing errors due to weathers, variable ambient environment and during maintenance period (Chien, Chu, Hsu, Tseng, Hsu, & Chen, 2003).

Besides using thermodynamics and statistical method, Bunyamin et al., 2013 achieved in predicting NOx emission in a combined cycle power plant by using genetic algorithm (GA) combined with linear regression (LR) method. This method, also known as hybrid method, also known as GA-LR works where GA is used to search for the optimum function until specific specification is met causing termination. The LR approaches a model function showing relation of an output dependent variable, y, with one or more explanatory attributes or inputs which denoted as x. The model function was able to estimate the output dependent variable from inputs data. The results using this prediction method maintain lowest possible error and allow reliable prediction of NOx for pollutant monitoring purposes.

Azid, Ripin, Aris, Ahmad, Seetharamu, & Yusoff, 2000, used feed forward back propagation artificial neural network method in predicting the emission of NOx, SO_2 and CO in a combined-cycle natural gas power plant. Artificial neural network (ANN) method were used by other several researchers such as Tronci, Baratti, & Servida, 2002, Zain & Chua, 2011, Botros and Chueng, 2010 and Botros, Selinger, & Siarkowski, 2009 in predicting the flue gas emission from power generation be it combined-cycle power plant or coal fired boilers. The artificial neural network (ANN) is based on the working process of human brain in analyzing and determining the decision after knowing and relating the information given (Azid, Ripin, Aris, Ahmad, Seetharamu, & Yusoff, 2000). ANN is based on a process where an output can be predicted from various inputs. Typical neural network consists of sets of inputs, set of outputs and weighting function. Based on the available data, the network is trained to refine the correlation between inputs and outputs. After the network was trained, it can be fed with any unknown input and able to predict the output with high degree of accuracy. Most research done for the Predictive

Emission Monitoring System (PEMS) deploy Artificial Neural Network (ANN) method and the results is very low in error compared to physical sensors or Continuous Emission Monitoring System (CEMS) readings.

The progress and development of Artificial Intelligent (AI) as a method for optimization, decision making and prediction provide benefits to the Predictive Emission Monitoring System (PEMS). The diversified method to predict the flue gas emission using AI started with the ANN and now studies were done using other AI concepts such as Support Vector Regression (SVR) with ant colony optimization (Zheng, Zhou, Wang, & Cen, 2008), Least Square Support Vector Regression (LS-SVR) (Zheng, Jia, Yu, & Yu, 2010) and many more. The development of AI prediction for modeling of flue gas emission provides wider diversification for PEMS and enhances the reliability of the predicted results.

2.2 Support Vector Machines

Support Vector Machines (SVM) is supervised learning mechanism with associated learning algorithms that analyze data and recognize patterns use for prediction and regression analysis. SVM able to analyze input data and predicts the form of output either linear classifier or non-linear classifier. The original SVM algorithm was first invented by Vladimir N. Vapnik in 1963 as linear classifier. Support vector machine will create hyperplane or set of hyperplanes in an infinite-dimensional space which can be use for prediction, regression or other task. The best hyperplanes represents the largest separation or margin between the two classes. A maximum-margin hyperplane exist when the distance from its nearest data point on each side is maximized.

Nonlinear classifier was introduce by Boser ,Guyon and Vapnik, 1992 by applying the kernel trick to maximum-margin hyperplanes. The resulting algorithm of every dot product is replaced by non linear kernel function. The common kernels include Polynomial (homogeneous or inhomogeneous), Gaussian radial basis function and hyperbolic tangent.

Hao Zhou et al. predicts an efficient NOx emissions model based on support vector regression (SVR) with ant colony optimization (ACO) and compares its performance with traditional modeling techniques such as back propagation (BPNN) and generalized regression (GRNN) neural networks. The predicted NOxemission from the SVR model, by comparing with the BPNN model, was in good agreement with those measured and were comparable with those estimated from the GRNN model.

Support vector machine is a good prediction method and it is used in wide application related to machine learning. Zheng, Zhou, Cen and Wang, 2006 used support vector regression for combustion optimization of a coal fired boiler. SVR was used to model the relationship between NOx emissions and operational parameters of the utility boiler. Zheng et al. carried out the test in two stages where in the first stage, they deploy SVR together with genetic algorithm. The predicted NOx emissions from SVR-GA model were in good agreement with the measured readings. In second stage, they combined SVR with ant colony optimization (ACO), genetic algorithm (GA) and particle swarm optimization (PSO). The hybrid algorithm between SVR and other optimization except PSO can effectively reduce NOx emissions of the coal-fired boiler below the legislation requirement of China. Comparison among the various combination of SVR and optimization algorithm shows that hybrid ACO outperforms GA and PSO in terms of the quality of solution and the convergence rate.

Besides that, SVR was used for multi-view face detection and recognition by Li, Gong and Liddlell, 2000. Wu, Ho and Lee, 2004 used SVR to predict accurate travel-time which is vital for intelligent transportation systems and advanced traveler information system. Both studies produced good results where Li et al., 2000 obtain above 90 percent recognition accuracy and Wu et al. results show that SVR predictor significantly outperforms the other baseline predictors for travel time prediction.

3.0 Research Methodology and Designs

This research has been conducted with objective to create the model to predict the NOx value from gas turbine flue gas emission. The variables for the prediction comes from the gas turbines parameters such as the loading of the gas turbine, rotor speed, IGV position, two gas control valves position, compressor inlet temperature, fuel stroke reference, compressor discharge pressure and average exhaust temperature.

The prediction for NOx emission was carried out on GT2 of Putrajaya Power Station located in Putrajaya, Malaysia. The gas turbine is an open cycle gas turbine used as peaking machine.

3.1 Data collection method

In this research, the data used came from the instrumentation measuring all the variables at the gas turbines. The dependent variable, NOx was obtained from the continuous emission monitoring system (CEMS). The independent variables were obtained from the gas turbine parameters such as megawatt meter, speed sensors, linear variable differential transformer (LVDT) for IGV and valves position feedback, resistance temperature detector (RTD), pressure sensor and calculated distributed control system value. The data from the sensors and analyzer fed to the data acquisition system and recorded in the server.

Since GT2 Putrajaya Power Station is a peaking machine, the loading pattern is daily startup and shutdown to support the grid system especially during peaking hour. The data collected for this study are from daily startup and shutdown. The complete process of startup and shutdown of the gas turbine provide all scenarios that affect the NOx readings and beneficiary for the supervised learning. The data collected for the SVM training are summarized in Table 1.

Table 1: Details of data collection for supervise training

No	Data	Total
1.	NOx (from CEMS)	1440
2.	9 Attributes (MW, CTIF, IGV,TNH, GCV, SRV, TTXM, CTD & FSR2)	12960

3.2 Simulation

The data was run for supervised learning using MATLAB and LIBSVM (Hsu, Chang, & Lin, LIBSVM: A library for support vector machines, 2013) to obtain the optimum model that produce the lowest mean squared error for this specific machine. Initial tried out were established using radial basis function and polynomial. The objective is to create the model to predict NOx emission from the nine important gas turbine parameters with highest average accuracy between NOx from CEMS (actual) and predicted NOx.

4.0 Result and Discussion

The data set was trained using MATLAB and LIBSVM 3.17. In the first stage, the data set was trained using radial basis function (RBF) kernel as proposed by Hsu, Chang and Lin, 2010. The constant was adjusted to obtain the lowest mean squared error (*MSE*). The trending between the measured NOx and predicted NOx using RBF are shown in Figure 1 together with the correlation plot as in Figure 2.

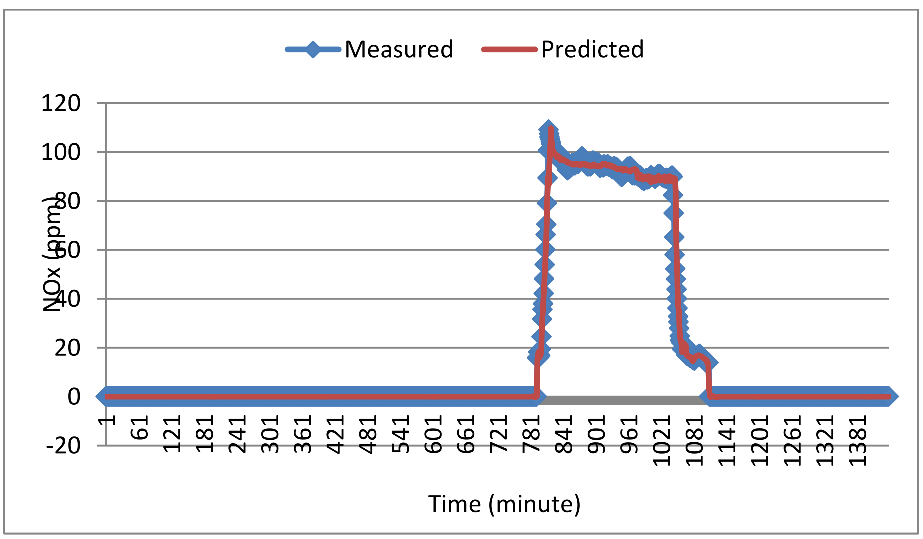

Figure 1: Measured Vs. Predicted NOx graph using RBF

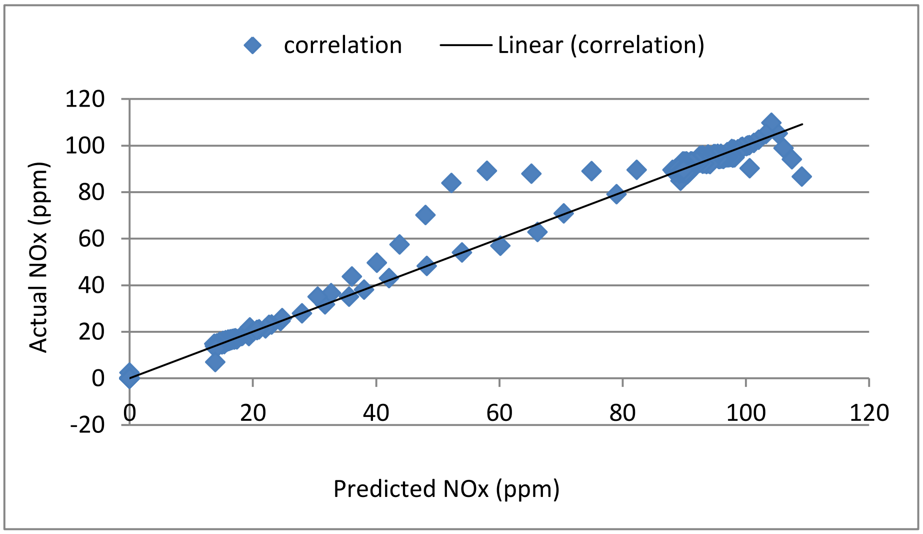

Figure 2: Correlation plot for NOx prediction model using RBF

The model to predict NOx emission using RBF is shown below.

$$y(x)_{GT2,NOx} = \sum_i \left(-\alpha_i + \alpha_i^*\right) \exp\left(-0.00001811 \left\| x_i - x_j \right\|^2\right) + b \qquad [1]$$

where, $\left(-\alpha_i + \alpha_i^*\right)$ and b is the parameter obtain after performing SVM training, γ is parameter needed to tune for optimize output, x_i is a training sample and x_j is the input data for prediction

In second stage, the data set was trained using polynomial kernel. The polynomial constants were adjusted to obtain the best *MSE*. The trending between measured NOx and predicted NOx using polynomial kernel are shown in Figure 3 and correlation plot in Figure 4.

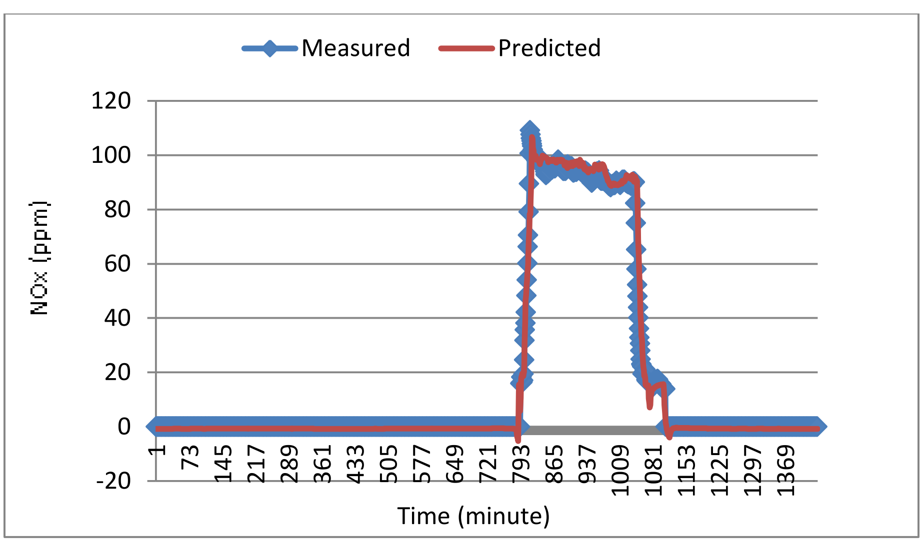

Figure 3: Measured Vs. Predicted NOx graph using polynomial

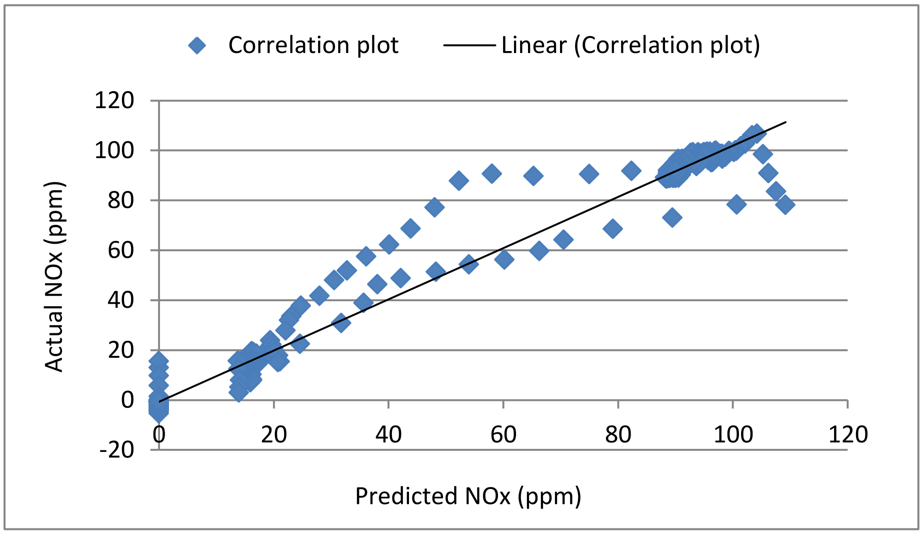

Figure 4: Correlation plot for NOx prediction model using polynomial

The NOx prediction model using polynomial is shown below.

$$y(x)_{GT2,NOx} = \sum_i \left(-\alpha_i + \alpha_i^*\right)\left(0.00007716 x_i^T x_j + 0.079\right)^2 + b \qquad [2]$$

Where, $\left(-\alpha_i + \alpha_i^*\right)$ and b is the parameter obtain after performing SVM training, γ, r and d is a parameter needed to tune for optimize output, x_i is a training sample and x_j is the input data for prediction.

The prediction error is calculated using mean square error (*MSE*),

$$MSE = \frac{\sum_{n=1}^{N} \left(\left|AEV - PEV\right|_n\right)^2}{N} \qquad [3]$$

Where, *AEV* is the actual emission value, *PEV* is the prediction emission value and *N* is the total prediction count.

The prediction accuracy is calculated using percentage of average accuracy (*%AA*),

$$\%AA = \frac{\sum_{n-1}^{N} \left|PEV\right| n}{\sum_{n-1}^{N} \left|AEV\right| n} \times 100\% \qquad [4]$$

The constants used for both model are simplified in Table 2 together with the *MSE* and *%AA*.

Table 2: Training constants and results for RBF and polynomial

Kernel	*n*	*C*	*g*	*r*	*d*	*MSE*	*AA (%)*
RBF	0.05	7505	0.00001811	-	-	3.44288	98.14
Polynomial	0.999	5	0.00007716	0.079	2	9.32085	96.95

The RBF kernel training provides better prediction for this data set compared to polynomial kernel.

5. Conclusion

This research focus on prediction of NOx using support vector (SVM) method and developing the prediction model that provide the best accuracy for this dedicated machine. The prediction method could provide reliable readings which will not be affected by harsh environment condition (Swanson & Lawrence, 2009) and cost effective compare to CEMS Chien et al. The RBF model provides better prediction compare to polynomial model. Further studies on other gases as regulated by DOE provide complete solution to power generation in monitoring the flue gas emission from the combustion engines.

Acknowledgement

The author would like to thanks the support from A.P. Dr. Mahmoud Almsafir from University of TenagaNasional and Mr. AzmanZahari from Putrajaya Power Station.

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