COMPARING EMPIRICAL, STATISTICAL, AND NEURAL NETWORK MODELS CALCULATING NOX EMISSIONS FROM GAS TURBINES

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Measurements of NOx levels and process data have been performed on two offshore gas turbine installations in Norway, a standard aeroderivative system and a dry low-emission system. The data have been used to develop statistical and neural network NOx emission models, and comparisons with existing empirical models, i.e., so-called physical or first principles models, have been made. Model comparison results show that the neural network models perform best, but also, some statistical models are able to reproduce the measured emission levels quite well. Empirical models are not able to reproduce the emission levels from the two gas turbines satisfactorily.

Keywords: NOx; PEMS; Gas turbine; Neural network; Experiments; Modeling

INTRODUCTION

Reduction of NOx emissions from various combustion applications, including boilers and gas turbines, is an area of continuous interest for both authorities and research communities worldwide. Advances in NOx emission reduction measures tend to be followed by increasingly stringent NOx emission limits. Also, attaching a price tag on NOx emissions is becoming increasingly common. This puts increasing demands on the reliability and accuracy of the methods used to monitor the NOx emission levels, which is the focus of this article.

Continuous emissions monitoring systems (CEMS) have been used for a long time for determining accurate NOx emissions from combustion systems like...
boilers and gas turbines. A cost-effective alternative is to use predictive emissions monitoring systems (PEMS). A PEMS consists of mathematical models of a process unit that use measured or calculated process data as inputs to determine emissions as outputs. Using PEMS, different alternatives concerning the use of models exist. All models have to be developed based on simultaneous measurements of process data available for a plant and targeted emissions. A model can be made up of different complexity regarding the number of parameters involved, in addition to a validation of input process data to the models. Pavilion Technologies, as one example, has experience implementing PEMS based on neural network models over the past 10 years in the United States and has over 210 PEMS in operation. Approval by the U.S. Environmental Protection Agency (EPA) is needed for these PEMS installations.

A PEMS model can be claimed to be a partly physical model. However, real physical/chemical models (hereafter called physical models) concerning NO\textsubscript{x} emissions are very complex. In a conventional gas turbine, the thermal NO\textsubscript{x} formation mechanism will dominate, while in a low-NO\textsubscript{x} gas turbine, prompt NO\textsubscript{x} formation or NO\textsubscript{x} formation through the nitrous oxide mechanism may become relatively increasingly important. In addition, NO\textsubscript{x} formed may be reduced to some extent or may be converted to NO\textsubscript{2}. This complicates severely any physical model trying to reproduce or predict the NO\textsubscript{x} emission levels from a specific gas turbine.

Models for NO\textsubscript{x} emission reproduction and prediction can be divided into three types: (1) empirical models, with some kind of physical interpretation, derived by some type of curve-fitting software, with or without statistical analysis; (2) statistical models, with much less focus on physical interpretation, using some form of statistical software/procedure for evaluation of the experimental data, often taking into account input and output data uncertainties, and deriving the model; and (3) artificial intelligence models, which include neural network models, with no focus on physical interpretation but with extensive focus on analysis of the relation between input and output data, using extensive data sets and statistical analysis and model verification/testing. Usually, some kind of self-learning capability is included, which can be utilized to continuously and automatically improve the models.

It is important that a neural network PEMS includes the use of a sensor validation system consisting of neural network models prior to the emissions model to ensure that only valid sensor data are used to create emissions data. Such a sensor validation system should provide substitute sensor values for failed sensors so that the PEMS can continue to provide valid data. PEMS that do not include this type of robust sensor validation system are generally limited to the detection of failed sensors, resulting in PEMS downtime.
An extensive review of artificial intelligence models, including neural network models, has been performed by Kalogirou (2003).

**METHODS**

**Experimental and Measurement Procedures**

The models are developed based on experimental results from offshore gas turbines on the Åsgard B (ASGB; GE LM 2500 PR DLE gas turbines) and Sleipner A (SLA; GE LM 2500 PE gas turbine) platforms, where Statoil is the platform operator. On the ASGB platform, two identical gas turbines were used: a gas compression turbine (compressor B) working in a high load range and a generator turbine (generator A) working at lower and more variable loads. The experimental results were collected in a Statoil ASA financed project carried out by Axess Energy and Environment AS (AEM), where the goal was to collect enough data for deriving PEMS models for the gas turbines in question.

The measurements were carried out with synchronized registration of emission concentrations and operational parameters. The loads where the measurements were made were chosen from the normal operational range for the gas turbines, *i.e.*, 50–105% for the GE LM 2500 PE gas turbine and evenly spread loads between maximum and minimum load for the GE LM 2500 PR DLE gas turbines in both AB (pilot and outer fuel ring on) and ABC (inner, pilot, and outer fuel ring on) operational modes.

The emission measurement system and instruments were according to ISO 11042-1 (International Organization for Standardization, 1996).

The flue gas species measured in dry flue gas were NO\textsubscript{x} (NO + NO\textsubscript{2}), CO\textsubscript{2}, CO, and O\textsubscript{2}, measured using a Horiba PG-250 multicomponent analyzer, and the fuel gas compositions were measured by Statoil using a gas chromatograph. Potential operational model input parameters that were measured or calculated and reported by the gas turbine control system include the fuel gas flow \((m_f)\), fuel gas temperature \((T_f)\) and pressure \((p_f)\), compressor inlet temperature \((T_2)\), combustion chamber exit bulk temperature \((T_4)\), gas generator outlet temperature \((T_{54})\) and pressure \((p_{54})\), compressor inlet pressure drop \((p_1 - p_2)\), compressor outlet temperature \((T_3)\) and pressure \((p_3)\), gas generator speed (NGG), power turbine speed (NPT) and output \((P)\), and air flow through the compressor \((m_a)\). Also, the compressor bleed (bleed) and the variable stator vane position (VSV) were reported.

In addition, ambient conditions — temperature \((T_{amb})\), pressure \((p_{amb})\), and relative humidity \((\varphi)\) — were measured manually and by a weather system.

The compressor inlet pressure \((p_2)\) was calculated from \(p_1 = p_{amb}\) and \(p_1 - p_2\). The ambient air absolute humidity (AH) was calculated from the ambient con-
ditions. The combustion chamber exit bulk temperature \((T_4)\) was only reported for the ASGB platform. The reported \(T_4\) value was a calculated value, using a heat balance calculation procedure implemented in the gas turbine control system. For the SLA platform, \(T_4\) was calculated in this work.

The signals from the gas turbine control system and the flue gas analyzer were recorded each second by an AEM portable computer. Average emission and process parameter values were calculated from the instantaneous values for each load, from a time period of about 10 min, with close to constant operating conditions.

**Emission Data Treatment and Uncertainties**

The measured flue gas composition was used to convert the \(\text{NO}_x\) emission level to 15 vol.% \(\text{O}_2\) in dry flue gas by using equation (1), and the converted \(\text{NO}_x\) emission level was then modeled:

\[
\text{NO}_x = \frac{O_{2,\text{air}} - 15}{O_{2,\text{air}} - O_2} \times \text{NO}'_x
\]  

where

- \(\text{NO}_x\) \(\text{NO}_x\) at 15 vol.% \(\text{O}_2\) in dry flue gas (ppm)
- \(O_2\) \(O_2\) measured in dry flue gas (vol.%)
- \(O_{2,\text{air}}\) \(O_2\) in dry air, \(= 20.9476\) (vol.%) (International Organization for Standardization, 1975)
- \(\text{NO}'_x\) \(\text{NO}_x\) measured in dry flue gas (ppm)

Uncertainties in the converted \(\text{NO}_x\) emission level are connected to both the measured \(O_2\) and \(\text{NO}\) levels. A global combustion equation can be balanced based on either the measured \(O_2\) or \(\text{CO}_2\) level. Hence the \(O_2\) level can also be calculated from a measured \(\text{CO}_2\) level. This calculation is not influenced by gas turbine air cooling. In addition to the \(\text{CO}_2\) measurement uncertainty, additional uncertainty is then connected to the elemental fuel composition and emissions of incomplete combustion (CO in our case). These two additional uncertainties are, in this work, small.

The total uncertainty in the converted \(\text{NO}_x\) emission level was calculated in this work for all the ASGB and SLA experiments using the Excel spreadsheet Fuelsim-Average v1.1 (Skreiberg, 2002) (available at http://www.ieabcc.nl/) and equation (2). On the basis of this total uncertainty analysis, the \(O_2\) levels calculated from the measured \(\text{CO}_2\) levels were used, instead of the measured \(O_2\) levels:

\[
\Delta \text{NO}_{x\text{tot}} = \left( \sum_{i=1}^{n} \Delta \text{NO}_{x,i}^2 \right)^{1/2}
\]  

(2)
where

\[ \Delta \text{NO}_{x_{\text{tot}}} \] total uncertainty (%)

\[ \Delta \text{NO}_{x_i} \] single uncertainties in the calculated NO\textsubscript{x} emission level (%)

The uncertainties were also used to calculate weight factors linked to each NO\textsubscript{x} emission level, for use when developing the statistical models. The relative influence of the different experiments in the model optimization process is then adjusted based on the reliability/uncertainty connected to each single experiment. In this work, the influence of these weights on the statistical model selection process became negligible.

<table>
<thead>
<tr>
<th>Process parameter</th>
<th>Transmitter/type</th>
<th>Measurement range</th>
<th>Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_3 )</td>
<td>GULTON STATAM</td>
<td>0–500 psia</td>
<td>±0.01% of range</td>
</tr>
<tr>
<td></td>
<td>PA3000–500–42–13–XX–XX–61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p_{54} )</td>
<td>GENERAL ELECTRIC 8TE 34 &amp; 8TE 37</td>
<td>0–275.80 psia</td>
<td>±0.075% of range</td>
</tr>
<tr>
<td>( T_3 )</td>
<td>K-type thermocouple</td>
<td>0–1100°C</td>
<td>±1°C in range</td>
</tr>
<tr>
<td>( T_{54} )</td>
<td>K-type thermocouple</td>
<td>0–1100°C</td>
<td>±1°C in range</td>
</tr>
<tr>
<td>NGG</td>
<td>RED LION IMP20–030</td>
<td>0–99999 rpm</td>
<td>±0.02% of range</td>
</tr>
<tr>
<td>Fuel</td>
<td>not reported</td>
<td>not reported</td>
<td>±1.5% of value</td>
</tr>
</tbody>
</table>

FIGURE 1 Average NO\textsubscript{x} emissions in parts per million at 15% O\textsubscript{2} in dry flue gas as a function of fuel consumption for the Åsgard B (ASGB) gas turbines.
As examples, uncertainties connected to some of the measured values for the ASGB gas turbines are given in Table I, and the calculated uncertainties for the NO\textsubscript{x} emission level is illustrated in Figure 1, showing the NO\textsubscript{x} emission level (parts per million at 15 vol.% O\textsubscript{2} in dry flue gas) as a function of the fuel consumption.

**Evaluation of Experimental Data to Be Included**

The experimental data were evaluated regarding their suitability for inclusion in the modeling approach. This included obvious error checking, parameter drift analysis, trend analysis, parameter relationships analysis, and uncertainty analysis. In addition, comparison with available so-called physical models was performed.

The data used in the modeling approaches were the NO\textsubscript{x} emission level at 15% O\textsubscript{2} in dry flue gas as the response parameter and process parameters as input parameters. The average fuel/air ratio (f) was calculated for each load using Fuelsim-Average v1.1 (Skreiberg, 2002). NO\textsubscript{x} formation will depend directly or indirectly on a number of these input parameters. In many cases, some input parameters are strongly correlated with other input parameters, which mean that the inclusion of both input parameters is not helpful in a simple statistical model. However, parameter relationships can be used to calculate missing or believed to be unreliable parameters, either through simple relationships or through other relationships like thermodynamic relationships for the compressor or the turbine.

Selected examples of relationships between input parameters are shown for the ASGB gas turbines in Figure 2.
Modeling Approach

A number of models were developed, using one or more input parameters. Comparisons with so-called physical models developed by Røkke, Hustad, and Berg (1993) and Bakken and Skogly (1995) were done for the SLA gas turbine. The Røkke et al. (1993) model is given in equation (3):

\[
NO_x = 18.1 \left( \frac{p_3}{p_2} \right)^{1.42} \cdot m_a^{0.3} \cdot f^{0.72} = 18.1 \left( \frac{p_3}{p_2} \right)^{1.42} \cdot m_f^{0.3} \cdot f^{0.42} \quad (3)
\]

where

- \( NO_x \): NO\(_x\) at 15 vol.% O\(_2\) in dry flue gas (ppm)
- \( p_3 \): compressor outlet pressure (bars)
- \( p_2 \): compressor inlet pressure (bars) mass airflow through compressor (kg/s)
- \( m_f \): fuel consumption (kg/s)
- \( f \): fuel/air ratio (kg/kg)

The Bakken and Skogly (1995) model is given in equation (4):

\[
NO_x = 62 \cdot p_3^{0.53} \cdot f^{14} \cdot \exp \left( \frac{-635}{T_4} \right) \quad (4)
\]

where

- \( NO_x \): NO\(_x\) at 15 vol.% O\(_2\) in dry flue gas (ppm)
- \( p_3 \): compressor discharge pressure (pascal)
- \( f \): fuel/air ratio (kg/kg)
- \( T_4 \): calculated combustion chamber exit bulk temperature (°C)

Empirical models, i.e., so-called physical or first principles models, are relatively simple models, including one or only a few process parameters. The models are usually selected so that they are able to capture an expected physical behavior of the emission level, while it is the model coefficients that are the subject of optimization, using selected physical constraints. For NO\(_x\) emission levels from conventional gas turbines, parameters that can be related to the strong temperature dependence of the thermal NO\(_x\) formation are selected. In addition, a pressure and residence time influence may be included. However, it is not straightforward to separate these influences from the temperature dependence, and especially not in simple models. A prerequisite of the so-called physical models is that the NO\(_x\) emission level should increase with increasing temperature, pressure, and residence time according to the thermal NO\(_x\) formation theory. This puts constraints on the model coefficients to prevent unphysical behavior.
Stastical models put much greater focus on statistical treatment of the relationship between the input parameters and the model output. All available input parameters may be tested, usually using a statistical software package and a least squares minimization procedure, where, also, weighting based on uncertainty can be taken into account. Various statistical results can be calculated and tests can be run to arrive at a conclusion regarding the suitability and significance of the single input parameters in a model. In an automatic procedure, the significant input parameters are found that satisfy a selected set of statistical criteria. The model developer can influence the model development process by changing the criteria, the weights, or the input parameters to be included in the optimization procedure.

In the statistical modeling approach, NO\textsubscript{x} emissions in parts per million at 15 vol.% O\textsubscript{2} in dry flue gas were modeled using both the polynomial curve fitting capabilities in Microsoft Excel and a multivariable optimization method based on least squares minimization in the statistical software program MINITAB v13.32. The process parameters were checked for possible correlation against the NO\textsubscript{x} emission level in parts per million at 15 vol.% O\textsubscript{2} in dry flue gas using both polynomial fits in Excel and the stepwise regression and best subsets options in MINITAB, which has extensive possibilities for regression analysis included. The stepwise regression option may automatically step through the selected process parameters to find the optimum model that satisfies certain goodness of fit criteria. In short, lack of fit tests is carried out automatically. Using the best subsets option, lack of fit tests must be carried out manually. Neither the stepwise regression nor the best subsets options allow weighting of the response variable, in our case, the NO\textsubscript{x} emission level. However, if the differences in the weight factors for the different experiments are not large (as in this work), this can be regarded as an acceptable simplification in a first screening approach. When the potential best models are identified, each model can also be optimized using weighting of the response variable through the regression option in MINITAB. Various statistical analysis data were calculated for each model.

All models were ranked initially based on a maximum degree of freedom adjusted $R^2$ (DOF $R^2$); however, only $R^2$ is presented in this article for the selected models. As a fit becomes more ideal, the $r^2$ values approach 1. The reader should note that two definitions of DOF $R^2$ exist in literature. The definition used in MINITAB is used in this work:

$$DOF R^2 = 1 - \frac{SSE \cdot (N - 1)}{SSM \cdot DOF}$$  \hspace{1cm} (5)$$

$$R^2 = 1 - \frac{SSE}{SSM}$$  \hspace{1cm} (6)$$
where

\[ \text{SSE} \quad \text{sum of squared errors (residuals),} \quad = \sum_{i=1}^{N} (x_i - y_i)^2, \quad \text{where } x_i \text{ are model values and } y_i \text{ are measured values} \]

\[ \text{SSM} \quad \text{sum of squares about the mean,} \quad = \sum_{i=1}^{N} (y_i - \bar{y})^2, \quad \text{where } \bar{y} \text{ is the mean of the measured values} \]

\[ N \quad \text{total number of data sets used to develop the models} \]

\[ \text{DOF} \quad \text{degree of freedom,} \quad = N - m, \quad \text{where } m \text{ is the number of coefficients in the model (including the constant term)} \]

Additionally, the relative accuracy (RA) value, frequently used to evaluate/limit models in PEMS, was calculated for all models. This value should be less than 10% for NO\textsubscript{x} (U.S. Environmental Protection Agency, 2005) (available at http://www.access.gpo.gov/cgi-bin/cfrassemble.cgi?title=200240). The RA value is defined as

\[ RA = \frac{\bar{d} + |cc|}{\bar{y}} \times 100\% \tag{7} \]

where the arithmetic mean error value \( \bar{d} \) and the confidence coefficient \( cc \) are defined as

\[ \bar{d} = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i) \tag{8} \]

\[ cc = t_{0.975} \cdot \frac{S_d}{\sqrt{N}} \tag{9} \]

where

\[ t_{0.975} \quad 2.5\% \text{ error } t\text{-value (one-tailed)} \]

\[ S_d \quad \text{standard deviation} \]

\( S_d \) is defined as

\[ S_d = \sqrt{\frac{\sum_{i=1}^{N} (x_i - y_i)^2 - \left( \sum_{i=1}^{N} (x_i - y_i) \right)^2}{N}} \tag{10} \]

A number of other statistical values may be calculated, and various statistical tests may be carried out. The lack of fit test carried out automatically or manually using MINITAB is regarded as sufficient in this work, in addition to evaluation of the statistical values previously defined.
Uncertainties in process parameters, and not only the calculated emission level, should ideally be accounted for when developing the models. However, only uncertainties in the response variable (the NO\textsubscript{x} emission level) in the models can, through weighting, be taken into direct account. The possible significant influence of uncertainties in the process parameters on the choice of optimal models must be evaluated manually.

Neural network models were made using the Pavilion Software CEM program, applying nonlinear models and output and using two hidden layers, as illustrated in Figure 3.

The nonlinear model is given in equation (11), and the nonlinear output is given in equation (12):

\[
\begin{align*}
    a_i &= f_i \left( \sum_{i=1}^{I} (W_{ik} a_k + b_i) \right), \text{ where } f_i(z) = \frac{1}{1+e^{-\lambda_i z}} \\
    y_j &= f_j \left( \sum_{i=1}^{K} (W_{kj} a_k + b_j) \right), \text{ where } f_j(z) = \frac{1}{1+e^{-\lambda_j z}}
\end{align*}
\]

where \( W, b, \) and \( \lambda \) are known as weights, bias, and slope.

The model generation, or training, process can be described by five steps: 
(1) all weights and parameters are set to small random numbers; 
(2) all inputs and outputs are normalized based on the minimum and maximum values; 
(3) a nonlinear transfer function is applied to the weighted sum of the normalized in-
puts to calculate each processing element’s output; (4) a recursive algorithm is used to adjust the weights; and (5) step 4 is repeated until a user-specified convergence is achieved.

RESULTS

Figure 4 shows the average NO\textsubscript{x} emission levels for each load for the SLA experiments, plotted as a function of the power in MW electric. As expected, the NO\textsubscript{x} emission level increases with increasing power. In general, the NO\textsubscript{x} emission level is lower than predicted by the Røkke et al. (1993) and Bakken and Skogly (1995) models. Optimizing the coefficients in these so-called physical models, while applying physical behavior constraints, did not improve the models significantly.

Statistical data for selected models are shown in Table II, a comparison of measured and modeled NO\textsubscript{x} emission levels for the ASGB gas turbines in combined ABC and AB mode for the best neural network and statistical models is shown in Figure 5, and a comparison of measured and modeled NO\textsubscript{x} emission levels for the SLA gas turbine for the best neural network and statistical models is shown in Figure 6.

In Figure 7, the average emission levels using the best neural network models for combined ABC + AB mode for the ASGB gas turbines and for the SLA gas turbine have been converted to gNO\textsubscript{x} (as NO\textsubscript{2}) per kilogram of fuel gas using

![Graph showing NO\textsubscript{x} emissions vs. power](image)

**FIGURE 4** Average NO\textsubscript{x} emissions in parts per million at 15% O\textsubscript{2} in dry flue gas as a function of power and comparisons with the Røkke et al. (1993) and Bakken and Skogly (1995) models.
### TABLE II  Statistical data for selected models for the NO\(_x\) emission level at 15% O\(_2\) in dry flue gas\(^a\)

<table>
<thead>
<tr>
<th>Model</th>
<th>Data sets</th>
<th>Parameters</th>
<th>(R^2)</th>
<th>RA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Røkke et al. (1993)</td>
<td>21</td>
<td>(p_3, p_2, m_\alpha, f)</td>
<td>0.545</td>
<td>7.497</td>
</tr>
<tr>
<td>Bakken and Skogly (1995)</td>
<td>21</td>
<td>(p_3, f, T_4)</td>
<td>0.730</td>
<td>5.224</td>
</tr>
<tr>
<td>SLA, simple statistical</td>
<td>21</td>
<td>(p_{54})</td>
<td>0.845</td>
<td>3.077</td>
</tr>
<tr>
<td>SLA, comprehensive statistical 1</td>
<td>11,095</td>
<td>(p_{54})</td>
<td>0.842</td>
<td>0.118</td>
</tr>
<tr>
<td>SLA, comprehensive statistical 2</td>
<td>11,095</td>
<td>(\ln(p_{54}), \exp(p_{54}), 1/p_{54}^4)</td>
<td>0.850</td>
<td>0.115</td>
</tr>
<tr>
<td>SLA, advanced statistical</td>
<td>11,095</td>
<td>(p_{54} + \text{nine others})</td>
<td>0.990</td>
<td>0.030</td>
</tr>
<tr>
<td>SLA, neural network</td>
<td>11,095</td>
<td>(p_{54} \text{ in three layers})</td>
<td>0.851</td>
<td>0.205</td>
</tr>
<tr>
<td>SLA, neural network</td>
<td>11,095</td>
<td>(p_{54}, \text{AH, VSV in three layers})</td>
<td>0.992</td>
<td>0.177</td>
</tr>
<tr>
<td>ASGB-ABC, simple statistical</td>
<td>21</td>
<td>(T_{54}, p_0)</td>
<td>0.984</td>
<td>0.476</td>
</tr>
<tr>
<td>ASGB-ABC, comprehensive statistical</td>
<td>12,260</td>
<td>(T_{54}, p_0)</td>
<td>0.975</td>
<td>0.022</td>
</tr>
<tr>
<td>ASGB-ABC, advanced statistical</td>
<td>12,260</td>
<td>(T_{54}, p_0 + \text{eight others})</td>
<td>0.983</td>
<td>0.019</td>
</tr>
<tr>
<td>ASGB-ABC, neural network</td>
<td>12,260</td>
<td>(T_3 \text{ in three layers})</td>
<td>0.879</td>
<td>0.441</td>
</tr>
<tr>
<td>ASGB-ABC, neural network</td>
<td>12,260</td>
<td>(T_3, \text{AH, bleed in three layers})</td>
<td>0.985</td>
<td>0.039</td>
</tr>
<tr>
<td>ASGB-AB, simple statistical</td>
<td>14</td>
<td>(\ln(T_{54}), \ln(\text{VSV}))</td>
<td>0.896</td>
<td>1.923</td>
</tr>
<tr>
<td>ASGB-AB, comprehensive statistical</td>
<td>8315</td>
<td>(\ln(T_{54}), \ln(\text{VSV}))</td>
<td>0.931</td>
<td>0.059</td>
</tr>
<tr>
<td>ASGB-AB, advanced statistical</td>
<td>8315</td>
<td>(\ln(T_{54}), \ln(\text{VSV}) + \text{eight others})</td>
<td>0.982</td>
<td>0.030</td>
</tr>
<tr>
<td>ASGB-AB, neural network</td>
<td>8315</td>
<td>(\text{NGG in three layers})</td>
<td>0.922</td>
<td>0.112</td>
</tr>
<tr>
<td>ASGB-AB, neural network</td>
<td>8315</td>
<td>(\text{NGG,AH, } p_3 \text{ in three layers})</td>
<td>0.988</td>
<td>0.118</td>
</tr>
<tr>
<td>ASGB-ABC + AB, simple statistical</td>
<td>40</td>
<td>(\ln(T_{54}), \ln(\text{bleed}))</td>
<td>0.425</td>
<td>4.167</td>
</tr>
<tr>
<td>ASGB-ABC + AB, simple statistical</td>
<td>40</td>
<td>(m_f, m_f^2, m_f^3, m_f^4)</td>
<td>0.807</td>
<td>2.411</td>
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<tr>
<td>ASGB-ABC + AB, comprehensive statistical</td>
<td>23,456</td>
<td>(\ln(T_{54}), \ln(\text{bleed}))</td>
<td>0.408</td>
<td>0.164</td>
</tr>
<tr>
<td>ASGB-ABC + AB, advanced statistical</td>
<td>23,456</td>
<td>(\ln(T_{54}), \ln(\text{bleed}) + \text{eight others})</td>
<td>0.885</td>
<td>0.072</td>
</tr>
<tr>
<td>ASGB-ABC + AB, neural network</td>
<td>23,456</td>
<td>(m_f \text{ in three layers})</td>
<td>0.815</td>
<td>0.808</td>
</tr>
<tr>
<td>ASGB-ABC + AB, neural network</td>
<td>23,456</td>
<td>(m_f, T_{54}, \text{NGG in three layers})</td>
<td>0.968</td>
<td>0.152</td>
</tr>
</tbody>
</table>

\(^a\)Simple statistical models were developed based on averaged values for each load, while comprehensive/advanced statistical models and the neural network models were developed based on the instantaneous values giving the averaged values.
Fuelsim-Average v1.1 (Skreiberg, 2002). Included also are the Norwegian Oil Industry Association (2000) constant emission level factors, which have been used as a method to estimate the emission levels from gas turbines and which clearly are a great simplification in overpredicting the NO$_x$ emissions from most gas turbines.

FIGURE 5 Comparison of measured and modeled NO$_x$ emission level (parts per million at 15 vol.% O$_2$ in dry flue gas) for the ASGB gas turbines in combined ABC and AB mode for the best neural network and statistical models.

FIGURE 6 Comparison of measured and modeled NO$_x$ emission level (parts per million at 15 vol.% O$_2$ in dry flue gas) for the Sleipner A (SLA) turbine for the best neural network and statistical models.
DISCUSSION

As can be seen in Table II, the statistical goodness of fit for the presented models differs significantly. As expected, the neural network models perform best, followed by the statistical models and the so-called physical models. The question is how significant these differences are for real systems and how advanced the models must become to be good enough. The advantages and disadvantages of the models, and their practical implementation and use, will depend on the application in question and the applied regulations.

Empirical (physical) modeling of NO\textsubscript{x} emissions is very challenging. Finding a model that adequately reproduces a set of measured NO\textsubscript{x} emission levels is rather easy; the challenging part is to make the model as general as possible. A number of factors influence the NO\textsubscript{x} emission level, and the relative importance of these factors will vary to a great extent, depending on operational conditions and the combustion application in question. The Røkke \textit{et al.} (1993) and Bakken and Skogly (1995) models are examples of proposed models that are quite simple, yet claim to be physical models. These models are only physical in the sense that they do predict an increasing NO\textsubscript{x} emission level when one of their included process parameters increases (assuming that the mass flow of air is replaced by the fuel/air ratio and the fuel consumption in the Røkke \textit{et al.} (1993) model). However, they fail as general models, even when thermal NO\textsubscript{x} is the dominating NO\textsubscript{x} formation mechanism. This could be seen for the SLA gas turbine.

FIGURE 7  Average measured fuel-specific NO\textsubscript{x} emission from the ASGB and SLA gas turbines and comparisons with the best neural network models and the Norwegian Oil Industry Association suggested emission factors: 10.47 g/Sm\textsuperscript{3} for conventional gas turbines and 1.89 g/Sm\textsuperscript{3} for low-NO\textsubscript{x} gas turbines.
However, this does not mean that the so-called physical models are not useful as empirical models, when the thermal NO\textsubscript{x} mechanism is the dominating NO\textsubscript{x} formation mechanism. They do include process parameters that directly or indirectly influence the NO\textsubscript{x} emission level, and they do behave physically to some extent, but they fail to agree on the process parameters of importance and also the relative importance of process parameters that are included in both models. In reality, the process parameters included in the models are not independent and cannot be changed independently. This also means that the models are very much locked to the process parameter relationships for the gas turbine(s) they were developed for. In general, so-called physical empirical NO\textsubscript{x} emission models tend to disagree on the physics resulting in NO\textsubscript{x} emissions.

With this in mind, the development and use of statistical models and neural network models can easily be justified. The purpose of these models is only to reproduce and thereafter predict the NO\textsubscript{x} emission level from a specific gas turbine. The models are not general models, but rather unit-specific models. A physical interpretation of such models is hardly possible, and often, changing one or more process parameters independently results in a NO\textsubscript{x} emission level that changes in the wrong direction from a physical point of view. However, the included process parameters are not meant to be changed independently. As such, the Røkke et al. (1993) and Bakken and Skogly (1995) models may be better models from a physical perspective, but when it comes to statistical goodness of fit, the pure statistical models outperform these so-called physical models.

The use of neural network models brings the statistical models a significant step forward since they can include, in general, more process parameter variations through the use of layers, an extensive sensor validation system, and many submodels, depending on the analysis of the input data and the selected black box road from the input to the output. As such, a neural network model is to some extent close to a complete PEMS system. The process parameter relationships within a neural network model are not unique. It is the treatment of the system around these relationships that makes a neural network model more powerful than single empirical or statistical models. If included in a proper PEMS, a system of advanced statistical models may perform as well as a neural network model.

In general, NO\textsubscript{x} emission formation and reduction is far too complex to be captured in a physical sense by any of these models, but empirical and statistical models may be developed and used for fast and adequate estimates of the NO\textsubscript{x} emission level for a specific gas turbine and are as such very useful in a PEMS. Alternatively, a PEMS can be built up around a more advanced modeling system, e.g., a neural network model.
CONCLUSIONS

$NO_x$ emission levels from a low-$NO_x$ and a conventional type gas turbine have been measured and modeled by empirical and statistical models, in addition to a neural network model, in this work. So-called physical models, e.g., the Røkke et al. (1993) and the Bakken and Skogly (1995) models, were found not to be satisfactory, even for the conventional gas turbine. For a better fit to the measurements, statistical models including one or more process parameters were developed. These models are base models for specific gas turbine types. For each individual gas turbine, the coefficients in the models must be calibrated. Backup models can in some cases be found by calculating missing or believed unreliable process parameters from process parameter relationships.

In addition, neural network models were developed to compare the performance of these models to the simpler models. The neural network models performed, in general, better than the simple statistical models in reproducing the $NO_x$ emission level from the two gas turbines and also somewhat better than the advanced statistical models.

In general, advanced statistical and neural network models can be developed that reproduce and predict the $NO_x$ emission level quite adequately. However, it is first when these models are put into a PEMS system that they become really useful. Since PEMS replace CEMS, the use of a sensor validation system will ensure the acceptability and accuracy of the PEMS data long term, as demanded by the air pollution control agencies.

The measurements clearly show that the method used up to now in Norway for estimating $NO_x$ emissions from gas turbines (the Norwegian Oil Industry Association method) by using a constant emission factor multiplied with the fuel consumption gives too high $NO_x$ emissions.

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References


