Enhanced Turbine Monitoring Using Emissions Measurements and Data Reconciliation

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Abstract

Standard monitoring within a gas-turbine based cogeneration system includes key flow rates, temperatures, pressures and turbine vibration. These standard measurements can be enhanced with continuous emissions monitoring to help pinpoint system problems. A combination of these measurements, a fast NO_x prediction model and data reconciliation constitute an improved monitoring and diagnostic tool that can quantitatively predict the existence of turbine problems (for example, damaged combustor nozzles) even when standard turbine monitoring indicates no problems exist.

1. Introduction

The cogeneration of heat and power is integral to many industrial processing sites. Cogeneration systems represent a large capital investment with costs approaching \$1MM/MW of installed capacity. The gas turbine is the heart of the cogeneration plant. For gas turbines, the early detection of many common problems is difficult, but of critical importance. Unexpected shutdowns of a gas turbine can result in a large increase in the electricity demand charge from the local utility. Such increases typically last one year.

Repair of the combustion chamber in a nominal 20 MW turbine can easily exceed \$¼MM. On a routine basis (per 4,000 hours of operation or every six months) turbines are physically inspected to ensure that their bearings and rotors are intact, e.g., no damaged blade tips. Also, turbine vibration is continuously monitored to detect these same problems. A large body of literature is devoted to the importance of performance monitoring and early problem detection. The components of monitoring and detection include data extraction, fault detection, fault location and prognosis [1-4]. Much of the current literature focuses on fault location algorithms which can be broken down into pattern recognition methods such as fuzzy logic [5, 6], genetic algorithms [7], Bayesian belief networks [8-10], and neural networks [11-14] and model identification methods such as Kalman filtering [15] and weighted least squares [16-18]. But despite continuous developments in all of these physical and computational techniques, serious gas turbine problems can still quickly develop before corrective actions can take place. For example, fuel nozzles can develop internal cracks that may not immediately affect the gross (vibrational or temperature/pressure) performance of the gas turbine. Such problems are not immediately detectable by standard performance monitoring/diagnostic tools.

In this work we present an improved diagnostic tool to indicate the early onset of problems in a turbine system by utilizing measured NO_x emissions. The quantity of emissions, including NO_x , CO , SO_2 , VOC and particulates, is regulated at most facilities, so highly accurate NO_x measurements in the exhaust stack are available. As an added benefit, early detection of turbine problems by this method can also help prevent emissions violations. This work significantly contributes to fault simulation methodology by coupling the thermodynamically consistent GRI-Mech 3.0 for natural gas combustion to emissions measurements and engine performance. This deterministic method does generate an easy to implement strategy involving polynomials, because it is just an empirical fit of observed emissions. The current model (using GRI-Mech 3.0) accounts for 53 species and 325 reactions.

All useful diagnostic tools require highly reliable data. Gross error detection and data reconciliation are established techniques to ensure that plant data (chemical and petrochemical, mineral processing, etc.) satisfy material and energy balances [19, 20], leading to improved accuracy. These techniques are of increasing importance to the power industry including nuclear power plants [21], coal-fired [22] and combined cycle power plants [23]. Data reconciliation can be used to establish validated cogeneration system operating conditions using the measured flow rates for steam production, natural gas, air, and water injection, along with measured temperatures and pressures. An accurate temperature within the turbine's annular combustion chamber is usually not measured, due to the harsh environment [24], but this temperature is obtainable (observable) from the data reconciliation process. In this work we formulate a chemical reaction model for a natural gas feed in order to relate measured NO_x emissions to the annular combustor temperature. Data reconciliation with the global test method is then used to identify problems within major components of the cogeneration system. At most installations, even if a change in NO_x emissions were detected, this change would not become part of the data reconciliation or used to help pinpoint where problems may exist, because an annular combustor performance model would also be needed.

2. Process Description

2.1 LSU's Cogeneration System

Louisiana State University installed a 20 MW cogeneration system in 2006 to help meet campus electricity and steam demands. The system utilizes a GE LM-2000 aeroderivative engine operating with natural gas fuel. Water injection is one of the technologies used to control the NO_x emissions [25]. Figure 1 depicts the cogeneration system, consisting of an air compressor, annular combustor, gas turbine, power turbine and heat recovery steam generator (HRSG). Ambient air (state 0) passes through a cooler to adjust its temperature to a nominal 520 R. Regardless of the ambient temperature, state 1 will always be ~ 520 R, because this helps maximize turbine performance. Water is the heat exchange fluid in the air cooler, chilled water used on hot days or chilled water produced otherwise. This consistent incoming air temperature at state 1 does influence modeling and observed NO_x . Natural gas, with compressed air and injected water, is burned in the combustor, which delivers hot exhaust gases to the gas generating

turbine (expander). We assume (for calculation purposes) that all the work done by the gas generating turbine powers the compressor. The power turbine is connected to an electrical generator. The HRSG includes both economizer and evaporator sections.

Figure 1: Gas turbine cogeneration system – air cooler, turbine system and HRSG

Water injection in the combustion chamber moderates the flame zone temperature, both reducing the NO_x and increasing the power output. The water exits with exhaust gas in the stack. The drawbacks of water injection include additional costs for treated water, but, more seriously, water injection can promote abnormal wear of the fuel injectors or the turbine blades.

A Vivicom Continuous Emissions Monitoring System (CEMS) monitored the NO_x emissions at the stack continuously. The CEMS pumps a sample from the stack, converts any NO_2 to NO , then measures the combined NO_x in the range of 0-450 ppmvd (ABB Limas 11UV photometric analyzer). The meter is calibrated daily with a bottled calibration gas (Airgas, Certified Standard). To measure the CO and any unburnt hydrocarbon emissions, the exhaust was sampled into evacuated 500 mL 316 stainless steel bombs. These samples were analyzed using an Agilent 490 Micro GC containing 5A molecular sieve and Porapak U columns. Analysis conditions were 10 min, 80°C, helium carrier gas. Fuel (natural gas) samples were also analyzed similarly, as NO_x and other emissions vary with fuel composition.

2.2 Standard Cogeneration System Diagnostic Tools

The flow rates, temperatures, pressures and turbine vibration monitored by the distributed control system can help identify any abnormalities in the combustor/gas turbine. A key diagnostic is the exhaust gas temperature spread at the power turbine inlet. As shown in Figure 2, 11 thermocouples at this location are mounted radially. Current diagnostic strategy is to flag a temperature difference greater than 150 F between any two thermocouples. For any temperature difference exceeding 200 F, usual practice is to shut down the turbine.

Figure 2: Temperature measurements at the power turbine inlet

Table 1 shows a typical set of data from the cogeneration system at LSU.

Table 1 Key measured values and variable definitions from LSU's cogeneration system

Name	Description	Value	Units	Standard Deviation
F_{Air}	Air flow rate	145	lb/s	20
T_1	Air T leaving Air Cooler	519.94	R	5
P_2	Air P leaving Compressor	253.38	psia	1
T_2	Air T leaving Compressor	1260.48	R	10
F_{NG}	Natural Gas flow	3.0139	lb/s	0.07
$F_{Water,Inj}$	Water Flow injected Combustor	3.145	lb/s	0.1
P_3	Products gas P leaving Combustion Chamber	253.38	psia	1
P_4	Products gas P leaving Gas Generating Turbine	56.9	psia	1
T_4	Products gas T leaving Gas Generating Turbine	1836.34	R	30
P_5	Products gas P leaving Power Turbine	14.82	psia	1
T_5	Products gas T leaving Power Turbine	1386.67	R	60
P_6	Products gas P leaving Evaporator	14.82	psia	1
T_6	Products gas T leaving Evaporator	914.67	R	50
P_7	Products gas P leaving Economizer	14.82	psia	1
T_7	Products gas T leaving Economizer	787.67	R	20
F_{Prod}	Combustion products flow rate	147.6208	lb/s	20

$\dot{W}_{Net}$	Net Power produced by power turbine	21.39	MW	
$\dot{W}_{Net}$	Net Power produced by power turbine	20273.04	Btu/s	0.01
$\dot{Q}_{CC, Loss}$	Heat loss in Combustion Chamber	1125	Btu/s	250
NO_x	NO_x ppm leaving in the stack	38	ppmvd	1
$F_{Water, Econ}$	Feed Water flow entering Economizer	24.4444	lb/s	1.2222
$P_{Water, Econ}$	Feed Water P entering Economizer	239	psia	1
$T_{Water, Econ}$	Feed Water T entering Economizer	677.67	R	30
$P_{Water, Evap}$	Heated Water P entering Evaporator	198	psia	1
$T_{Water, Evap}$	Heated Water T entering Evaporator	780.67	R	30
F_{Steam}	Steam flow	24.17	lb/s	0.725
P_{Steam}	Steam P	140.9	psia	NA
T_{Steam}	Steam T	821.67	R	1
$F_{Water, BlowD}$	Blowdown flow – saturated water	0.28	lb/s	0.1

In Table 1 the instrument standard deviations were determined either from manufacturer-provided data or from a large data sample when the system was at steady state [20].

3. Model Development – Developing an Improved Diagnostic Tool for Turbine Systems

To indicate the onset of problems in the turbine system and generally improve cogeneration system diagnostics, we will utilize existing NO_x measurements. But, in order to do this we must have a model which relates measured NO_x to the environment where it was created. This model must be both accurate and “fast” in order to be utilized within a “real-time” data reconciliation. There are three general modeling categories for coupling emission measurements to combustor performance: (1) empirical and semi-empirical models; (2) chemical reactor networks (CRN) utilizing GRI-Mech 3.0 [26] (or an equivalent detailed chemical kinetics mechanism); (3) models based on computational fluid dynamics (CFD). Generally computational time increases with each method in the order listed. CFD modeling of combustors requires thousands of control volumes currently necessitating the use of reduced kinetics mechanisms [27]. For this work we will utilize CRN modeling.

3.1 Data Reconciliation

The data reconciliation problem is,

$$\text{Minimize } f = \sum_{\substack{i, \text{measured} \\ \text{variables}}} \left(\frac{x_i^+ - x_i}{\sigma_i} \right)^2 \quad (1)$$

$$\text{Subject to: } g_k(x_i, y_j) = 0 \quad k = 1, \dots, K \quad (2)$$

where x_i^+ are the measured process variables, x_i are the reconciled values, σ_i are standard deviations of the measurement instrument, $g_k(x_i, y_j)$ are the material and energy balances, and y_j are unmeasured process variables.

For the cogeneration system we can write energy balances for the air cooler, compressor, combustion chamber, gas generating turbine, power turbine, and HRSG evaporator and economizer. We can write material balances for the combustion chamber and HRSG. We equate the energy balances for the compressor and gas generating turbine giving six energy balances and two material balances. We performed the data reconciliation using the measured variables provided in Table 1; additional details for performing data reconciliation are provided elsewhere [28, 29]. Reconciled values for measured variables including F_{NG} , F_{Air} , and $F_{Water,Inj}$ were determined. The exhaust gas temperature from the combustor, T_3 , is typically not measured as instrument life is short due to the harsh (high temperature) environment [24]. The data reconciliation itself determined a “best value” for T_3 , which can be classified as an unmeasured but observable variable. Here T_3 was determined from the energy balances around the combustion chamber and the compressor/gas generating turbine. This T_3 value itself does not constitute a better or new diagnostic tool; however, it proves useful in the reaction model. Also, in this data reconciliation formulation the measured NO_x was not used nor its value reconciled, as it does not directly appear in the primary energy and material balances around any of the unit operations.

Now we consider using the measured NO_x in the stack as part of a strategy to indicate the onset of problems in the combustor/turbine. As the distribution of air, water and fuel with respect to position changes in the flame zone of a combustor, a change in the NO_x emissions from the stack will ultimately be observed. For our improved monitoring/diagnostic tool we couple the measured NO_x emissions with the reconciled system variables (especially F_{NG} , F_{Air} , $F_{Water,Inj}$ and T_2) and the unmeasured temperatures of the combustor (T_{Flame} and also T_3) to diagnose combustor problems (e.g., the possibility of bad nozzles). This coupling, via a fast NO_x reaction model, requires understanding the gas turbine annular combustor details. Ultimately the fast NO_x reaction model will be used in the constraints (equation (2)), allowing NO_x emissions measurements to appear in the objective function (equation (1)). The key to the model is to establish a kinetically rigorous and thermodynamically consistent basis coupling NO_x emissions to the combustor performance. As detailed below, we used GRI-Mech 3.0 (which accounts for 325 reactions and 53 species) with 22 perfectly stirred reactors (PSR) to account for the combustor flame zone (here F_{NG} , F_{Air} , $F_{Water,Inj}$, T_{Fuel} , and T_2 are used) followed by a PSR and plug flow reactor in series to model the remainder of the combustor allowing determination of T_3 and NO_x . This model when used in conjunction with the material and energy balance constraints reflects both NO_x emissions and other variables (both measured and observed).

The Gas Turbine Annular Combustor

An annular gas turbine such as the GE LM-2000 mixes and combusts air, water, and fuel at high temperature and near constant pressure. Thirty fuel nozzles introduce both the water and natural gas fuel to the compressed air. The combustor is depicted in Figure 3. Compressed air mixes

and combusts with the fuel and water at the nozzles. In addition some compressed air flows inside and outside the annular combustor to help cool the combustor as well as help cool the shaft connecting the gas turbine to the compressor.

Figure 3: Cut-away view of the GE LM-2000 annular combustor

Figure 4 depicts a side view of the combustor along its length. The combustor can be modeled as three distinct zones: primary/flame, intermediate, and dilution. These compartmental models have been used previously to calculate the species concentrations and temperatures exiting turbine combustors [28, 30-35]. When using a chemical reactor network (CRN), the primary zone is usually modeled as multiple perfectly stirred reactors in parallel [30, 36-39], the intermediate zone as a single plug flow [37, 38] or perfectly stirred [30, 39] reactor, and the dilution zone generally as a plug flow reactor (PFR). The CRN used in this work is indicated in Figure 4b. The reaction kinetics in each zone, for natural gas combustion and NO_x formation, consist of the well-known GRI-Mech 3.0 representation [26].

Figure 4: (a.) Schematic side view of combustor depicting the three reacting zones [40, 41], and (b.) our CRN model of the combustor.

3.3 The Combustor Primary/Flame Zone

In the primary combustion zone, air, fuel and water are injected into a highly-turbulent environment. Both fuel and water are delivered through each of the fuel nozzles. Of the NO_x exiting the system is formed, 95+% is formed here. With one perfectly stirred reactor (PSR) representing the primary zone, there can only be a single equivalence ratio ϕ (fuel to air ratio normalized by the same ratio at stoichiometric conditions) for the zone. But when air and fuel mix, pockets of different equivalence ratios will be formed [42]. In a CRN we assume that the primary zone equivalence ratio can be approximated as a normal distribution about a mean [43]. For annular combustors, cold flow and CFD studies indicate an average equivalence ratio of 0.81 in the primary zone [42, 44]; however, average primary zone equivalence ratio values for all gas turbine combustors can range from 0.5 to 2.0 [45]. Experimental results for annular combustors [37, 46] also allow calculation of the primary zone equivalence ratio standard deviation when assuming a normal distribution. For a mean equivalence ratio in the primary zone of 0.81 the standard deviation of the equivalence ratio is found to be 0.38 [37, 46].

To represent the combustor using a CRN we follow the annular combustor modeling work of Allaire et al. [37] who used 16 PSRs in parallel to model the primary zone, followed by 3 PFRs in series to represent the intermediate and dilution zones. The use of 16 parallel PSRs was needed to account for measured CO and NO_x emissions when requiring $\Delta[CO]_{(i+1)} =$

$([CO]_{(i+1)} - [CO]_{(i)})/[CO]_{(i)} < 0.15$ and $\Delta[NO_x]_{(i+1)} < 0.05$, where i is the number of parallel PSRs. For our work, in order to similarly account for $\Delta[CO]_{(i+1)}$ and $\Delta[NO_x]_{(i+1)}$ we used 22 parallel PSRs in the primary zone. The total mass flow into the primary zone is divided equally among the 22 PSRs. In Figure 5, we show equivalence ratios (Figure 5a) and temperatures (Figure 5b) without water injection in these reactors.

Figure 5: Fig 5 a.) Equivalence ratio versus natural gas flow rate in PSRs 1-11; Fig. 5b.) Natural gas flow rate versus temperature in PSRs 1-11 (radial symmetry). The equivalence ratio is 0.81 ± 0.38 .

The different equivalence ratios result in different temperatures and NO_x emission rates in the PSRs. For each PSR we used the same residence time (0.0015 s), but different volumes, given the different temperatures. This residence time is computed from the primary zone geometry, but with some minor adjustment to match up measured versus predicted NO_x and CO . In Figure 5a the average equivalence ratio is 0.81 ± 0.38 .

In the primary zone, thermal NO_x , produced by oxidation of the nitrogen in air, is the dominant NO_x mechanism [47, 48]. We model the water injection as occurring in PSRs 6-17, those PSRs nearest to the centerline. Figure 6 shows that in PSRs 6-17 a water/fuel ratio of 1.34 is maintained, with a zero water/fuel ratio in PSRs 1-5 and 18-22. This water injection causes lower temperatures in PSRs 6-17, which affect the predicted NO_x and CO emissions. This assumed distribution gave a good match with experimental data and it was guided by our observation (discussed below) that damaged nozzles are often accompanied by abnormal water wear on the combustor walls.

Figure 6: Distribution of water in the primary zone during normal operation (radial symmetry is assumed)

3.4 Intermediate and Dilution Zones

In the intermediate zone, exhaust products from the primary zone mix with additional air. The intermediate zone is modeled as a single PSR of residence time 0.035 s, based solely on geometry. The temperature is high enough such that some oxidation of CO and H occurs, and a small amount of additional NO_x formed. No further NO_x is formed in the remainder of the system.

In the dilution zone, where additional air enters, the combustion products are cooled to avoid any degradation in the first stage of the turbine. The dilution zone is modeled as a single PFR of length = 6.3" (from geometric considerations). Overall then the entire combustor (primary, intermediate and dilution zones) is ~3.5" height x 75" width x 14" length.

At typical operating conditions (Table 1), the GE LM2000 uses 3.01 lb/s of natural gas fuel and 145 lb/s of air, a fuel/air ratio = 0.0208. In the primary zone at design conditions the fuel requires 63.7 lb/s of air (equivalence ratio = 0.81). The remaining air enters the intermediate and dilution zones and the turbine itself, to cool the blades. For calculation purposes we assumed 60% remaining air (48.8 lb/s) in the intermediate zone, 40% (32.5 lb/s) in the dilution zone. If the combustor is operating properly, the NO_x (lbs NO_x /lb-total) and temperature leaving the primary zone will be the *same* for all *total* fuel/air ratios as long as the primary zone equivalence

ratio is constant. The NO_x concentration leaving the intermediate zone depends upon the air flow to that zone and on the reaction kinetics to a smaller extent.

3.5 Solution Approach for the Annular Combustor

Our solution approach was to combine the detailed chemical kinetics of GRI-Mech 3.0 (53 species and 325 elementary reactions) [26] with the material and energy balances for the PSRs and PFR [49]. This approach allowed prediction of NO_x , CO and temperature from both zones. The energy balance and component material balances constitute a set of coupled ordinary differential equations [50], which were integrated using the CVODE (Lawrence Livermore National Laboratory) package [51]. Excel served as the pre- and post-processor [52] by calling CVODE as a dynamic link library.

NO_x emissions depend upon the inlet air temperature to the combustor, the air and water flow rates, and the natural gas flow rate and composition. Figure 7 shows the NO_x emissions predicted by the CRN (GRI-Mech 3.0 + PSRs + PFR models) as the fuel/air and water/fuel ratios change. The ratio ranges shown in Figure 7 were typical of operation of the cogeneration system, and they lead to measured and predicted NO_x emissions ranging from ~20 to 50 ppmvd.

Figure 7 NO_x emissions (ppm) versus fuel/air and water/fuel ratios

In Figure 8, the measured and predicted NO_x and CO emissions are compared as a function of the C/H ratio in the natural gas when the system is at typical operating conditions. The CRN model consistently over predicts NO_x emissions by ~ 2.5 ppmvd and under predicts the CO emissions by $\sim 7-8$ ppmvd; similar NO_x and CO results have been found by others [38]. The small change in NO_x emissions with fuel C/H is expected [38].

Figure 8 Measured versus predicted NO_x and CO as a function of natural gas C/H at typical operating conditions of $F_{NG} = 2.9-3.1$ lbs/s, $F_{Air} = 140-150$ lbs/s, $F_{Water,Inj} = 2.95-3.25$ lbs/s, with no fuel preheating.

The challenge then in developing an on-line diagnostic tool is coupling the predicted NO_x concentrations with actual combustor operation over the entire range of operating conditions shown in Figure 7. It is CPU expensive to directly couple the data reconciliation with the CRN/kinetics emissions modeling. For a typical set of process measurements, data reconciliation by itself can take 10,000+ iterations. A more tractable approach is to formulate narrow ranges for the measured variables that affect NO_x emissions, and then curve fit the emissions calculated from the CRN over each range. This curve-fitted, reduced model can then be combined with the data reconciliation without a significant increase in solution time, the combination results in a fast NO_x prediction model.

Polynomial Approximations for NO_x Emissions and Combustion Chamber Temperature

In the primary zone, fuel and air are combusted with a fixed fuel/air ratio, while the remaining air is fed into the intermediate and dilution zones, with $\sim 10\%$ of the total air used to cool the turbine blades. We assume for modeling and data reconciliation purposes that all air has been added by the end of the dilution zone and will be accounted for in the combustor energy balance.

Doing so has no effect on predicted NO_x or CO. We assign $\dot{Q}_{CC, Loss}$ (combustion chamber heat loss) to the dilution zone, but any temperature change here also has no impact on the amount of NO_x leaving the system, as verified kinetically.

If we assume $\dot{Q}_{CC, Loss} = 0$ we can calculate the adiabatic temperature at the dilution zone exit, $T_3^{adiabatic}$, by two methods. A simple combustor energy balance allows $T_3^{adiabatic}$ to be determined. But we can also predict both NO_x and a unique $T_3^{adiabatic}$ based on the primary and intermediate zone material and energy balances, along with the additional air flow rate to the dilution zone. The two values for $T_3^{adiabatic}$ will be virtually identical when using thermodynamically consistent kinetics databases and recognizing that the dominant reaction is just methane combustion to carbon dioxide and water.

Simulation results for NO_x emissions versus $T_3^{adiabatic}$ for different water/fuel ratios and compressor discharge T_2 values (with $T_{Fuel} = 520$ R) are plotted in Figure 9. Along any curve in Figure 9, for example for $T_2 = 1206$ R and water/fuel = 0.8, as the fuel to air ratio increases both NO_x and $T_3^{adiabatic}$ will increase – both are uniquely determined, depending on fuel/air, water/fuel, T_2 and T_{Fuel} . But note that any selected $T_3^{adiabatic}$ can produce a range of NO_x values, and any selected NO_x value can produce a range of $T_3^{adiabatic}$ values. Therefore it is not possible to fit the data in Figure 9 to a single equation such as $T_3^{adiabatic} = f(NO_x)$.

Figure 9 NO_x versus $T_3^{adiabatic}$ as a function of water/fuel and T_2 values

However, it is possible to create a unique value for $T_3^{adiabatic}$ by multivariate curve fitting:

$$T_3^{adiabatic} = f \left[NO_x, \left(\frac{fuel}{air} \right), T_2, \left(\frac{water}{fuel} \right), \text{and } T_{Fuel} \right] =$$

$$T_3^{adiabatic} = A (NO_x)^a + B \left(\frac{fuel}{air} \right)^b + C (T_2)^c + D \left(\frac{water}{fuel} \right)^d + E (T_{Fuel})^e \quad (3)$$

For Equation (3) to also account for T_{Fuel} and represent the data in Figures 7 and 9, some 15 separate equations (regions of parameter space) were required. These equations and accompanying regions are provided in Table A1 of the Appendix.

The curve fits here allow us to couple the measured NO_x emissions (plus fuel, air and water flow rates and fuel and compressor discharge temperatures) to a unique $T_3^{adiabatic}$ and then a unique T_3 once $\dot{Q}_{CC, Loss}$ is accounted for. We can use the measured variables along with the measured NO_x emissions to predict $T_3^{adiabatic}$ and T_3 (Eq. (3)). We can also determine $T_3^{adiabatic}$ and T_3 by energy balance on the combustor. Errors will arise in data reconciliation as conflicts develop between measured variables and the reconciled values needed to satisfy the energy and material balances around the compressor, combustion chamber, and both turbines, and Eq. (3). Gross error detection combined with suspect measurement identification completes the development of the improved on-line diagnostic tool.

In data reconciliation $T_3^{adiabatic}$ must be adjusted to T_3 , the actual combustor exit temperature, by accounting for $\dot{Q}_{CC, Loss}$. To find the actual T_3 from $T_3^{adiabatic}$ we use:

$$\hat{h}_{Prod,3} = \hat{h}_{Prod,3}^{adiabatic} - \frac{\dot{Q}_{CC, Loss}}{F_{Prod}} \quad (4)$$

As the flow rates, NO_x concentration, T_2 and T_{Fuel} are varied during data reconciliation, $T_3^{adiabatic}$ is determined from the equations in Table A1 (Appendix), and $\hat{h}_{Prod,3}^{adiabatic}$ is determined using the Peng-Robinson equation of state [53, 54]. $\dot{Q}_{CC, Loss}$ and F_{Prod} are also varied during data reconciliation, and for each iteration $\hat{h}_{Prod,3}$ was calculated.

4. Results and Discussions – **Application of Improved On-line Diagnostic Tool for Cogeneration Systems**

4.1 Enhanced On-Line Diagnostic Tool for Turbine Monitoring

Before we provide examples utilizing the improved on-line diagnostic tool, we address the onset of combustor problems. As such problems develop, in particular due to poor distribution of fuel/water/air, emissions will increase, despite the fact that key measured variables may all remain within normal ranges (ranges reported in Figure 8).

As fuel nozzles become damaged due to blockage, cracks or abnormal wear, poor flow distribution of fuel and water can lead to increased NO_x emissions and higher local temperatures in the primary zone [55]. These higher temperatures can result in metal fatigue and further

erosion of the nozzles [56]. Figure 10 shows fuel/water injectors characterized by normal and abnormal wear; both nozzles were removed from the GE LM-2000 after 3 months (~2000 h) operation.

Figure 10 Fuel nozzles after ~3 months of operation. Fuel injection is through the 6 outer holes and water injection through the center 6 holes: a.) nozzle with normal wear; b.) nozzle with abnormal wear.

While figure 11 indicates that T_3 (determined from an overall energy balance around the combustor) might be the same regardless of nozzle conditions, a bad nozzle will result in a higher local T_{flame} , compared to a “design” nozzle, and the higher local T_{flame} will cause an increase in NO_x .

Figure 11 T_{flame} and the exit temperature from the combustor, T_3

Example 1 – Using Emissions Monitoring for Suspect Measurement Identification

In November measured NO_x emissions from the LSU cogeneration system gradually increased from 35 to 46 ppmvd (parts-per-million by dry volume) over three weeks. During this time period, no problems were detected by the standard cogeneration system diagnostics. The temperature difference between any two thermocouples at the power turbine inlet (Figure 2) remained less than 200 F, and no excessive turbine vibration was detected.

For calculation purposes representative data, with the exception of the increased NO_x emissions, can be found in Table 1. No fuel preheater was in use, so $T_{Fuel} = T_0$, and $T_{Water,Inj} = T_0$. Using the improved diagnostic tool, data reconciliation coupled with equation (3), we find the data reconciliation objective function (Eq. (1)) = 16.695.

The global test method [57] for gross error detection compares the least-squares objective function obtained in data reconciliation to a value of the chi-squared distribution, $\chi^2_{(1-\alpha)}(\nu)$, accounting for the desired error detection probability and the degree of redundancy (the number of material and energy balances around the cogeneration system):

$$GT = \sum_{\substack{i, measured \\ variables}} \left(\frac{(x_i^+ - x_i)}{\sigma_i} \right)^2 < \chi^2_{(1-\alpha)}(\nu) \quad (5)$$

In the distribution we used a 95% detection probability, $\alpha = 0.05$, and degree of redundancy $\nu = 8$. In the 8 balances we have utilized T_3 calculated from Eqs. (3) and (4). Here $GT = 16.695$ and $\chi^2_{(1-\alpha)}(\nu) = 15.507$, so gross errors are detected ($GT > \chi^2_{(1-\alpha)}(\nu)$).

The measurement test (MT) can pinpoint the most probable suspect measurement. The MT values were determined using Mah's (1990) procedure.[19]

$$MT_i = \frac{|a_i|}{\sqrt{V_{ii}}} \quad (6)$$

where $a_i = (x_i^+ - x_i)$ is an element of a , the adjustment vector, and V_{ii} is on the diagonal of the covariance of a ,

$$V = cov(a) = Q A^T (A Q A^T)^{-1} A Q \quad (7)$$

Q is the variance-covariance matrix (a diagonal matrix consisting of σ_i^2), and A is the incidence matrix of the linearized constraints (the 6 linearized energy balances and 2 material balances). When a gross error is detected, the measurement test (Eq. (6)) points to the most likely suspects.

However, it is recommended that non-redundant variables, i.e., those with $adjustability_i < \sim 0.05$, (a common industry standard) [58], or those below some other threshold value, be excluded from the gross error analysis. We calculate variable $adjustability_i = 1 - \frac{\sqrt{R_{ii}}}{\sigma_i}$, where $R_{ii} = Q_{ii} - V_{ii}$.

In order to use the *MT* method to identify the likely suspect variables, we first need to linearize the energy balances. Linearizing the energy balances is straightforward for the air cooler, compressor/gas turbine, evaporator, and economizer. These balances only involve $F \hat{h}$ terms and here $\hat{h} = f(P, T)$. The remaining two balances include $\dot{Q}_{CC, Loss}$ for the combustion chamber and $\dot{W}_{Net}$ for the power turbine in addition to $F \hat{h}$ terms. The $\dot{Q}_{CC, Loss}$ and $\dot{W}_{Net}$ are considered known “leaks” and can be fixed at the data reconciliation solution. Therefore only the $F \hat{h}$ terms for the combustion chamber and power turbine balances must be linearized.

A subtle problem arises when linearizing the energy balance for the combustor. Generally this balance would contain $(F_{NG}) (\hat{h}_{NG})$, but this can also be replaced by the lower heating value of the fuel $(F_{NG}) (LHV)$. Taking partial derivatives with respect to F_{NG} gives either LHV ($\sim 21,500$ Btu/lb for natural gas) or $\hat{h}_{NG}$ (~ -2000 Btu/lb when using the Peng-Robinson EOS with the enthalpy basis for each species its heat of formation at 77 F and 14.7 psia). This small value ($\hat{h}_{NG}$) for the second partial derivative leads to an adjustability for F_{NG} near 0, which is unrealistic as F_{NG} is the only system energy input. The combustor energy balance should be written:

$$F_{NG} (LHV) + F_{Air} (\hat{h}_{Air,2} - \hat{h}_{Air,ref}) + F_{Water,Inj} (\hat{h}_{Water,Inj} - \hat{h}_{Water,Inj,ref}) = (F_{Prod} \hat{h}_{Prod,3} - F_{Prod} \hat{h}_{Prod,ref}) + \dot{Q}_{CC, Loss} \quad (8)$$

And the fuel LHV determined using an EOS as:

$$LHV = \hat{h}_{NG} - \frac{F_{Prod} \hat{h}_{Prod,ref} - F_{Air} \hat{h}_{Air,ref} - F_{Water,Inj} \hat{h}_{Water,Inj,ref}}{F_{NG}} \quad (9)$$

The suspect measurement order is found as, first, $F_{Water,Inj}$, with $MT_{F_{Water,Inj}} = 19.57$, followed by the NO_x concentration, with $MT_{NO_x} = 3.04$, and then T_4 , with $MT_{T_4} = 3.00$. Recall that in Figure 8 the predicted NO_x concentration was 8 ppm above the experimental value of Table 1, and therefore this concentration might be expected to show the largest MT_i . However, the most likely suspect measurement appears instead to be $F_{Water,Inj}$.

It is common to exclude all virtually non-redundant variables (those with $adjustability_i < \sim 0.05$) [22, 58] from the measurement test analysis. According to this criterion $F_{Blowdown}$, F_{CW} , T_0 , T_1 , T_2 , $F_{Water,Inj}$, and T_{Steam} should be excluded from the measurement test analysis. The measurement test now results in NO_x concentration as the most suspect, after accounting for variable adjustability. The MT_{NO_x} came to 3.04, with T_4 as next most likely suspect measurement, with $MT_{T_4} = 3.00$.

These results indicate problems exist in the combustor, but with almost equal concerns about NO_x and T_4 measurement at the exit of the gas generating turbine. However, there are actually 11 replicate measurements of T_4 , enhancing the probability that the real source of problems is the combustor.

4.2 Predicting the Onset of Malfunctioning Nozzles

We have made the engineering simplification that the turbine annular combustor primary zone with 30 nozzles can be represented by a CRN consisting of 22 PSRs with known fuel/air distribution. Under normal operating conditions we assumed that the injected water was used by the PSRs representing the region near the combustor centerline, as indicated in Figures 6 and 12a. This assumed water distribution and the use of 22 PSRs in the primary zone gave the best agreement between experimental and predicted results for NO_x and CO emissions, as shown in Figure 8. To simulate actual nozzles going bad, we assumed that some water flow would be redistributed from the PSRs near the centerline to the PSRs representing the region closer to the wall. This assumption was based on the observation that malfunctioning nozzles tend to also erode the combustor walls. In Figure 12 we consider the case where 3 fuel/water injection nozzles have gone bad and are maldistributing water. There are 30 actual nozzles, so 10% of the water flow rate would be redistributed from PSRs 6-17 to PSRs 1-5 and 18-22 as shown in Figure 12. We also assume that the fuel/air or equivalence ratio of each PSR is unaffected by water redistribution.

Figure 12: a.) Water injection in the primary zone during normal operation; b.) Water injection in the primary zone with 3 bad nozzles (radial symmetry assumed).

In Figure 13 we plot the calculated NO_x emissions versus number of maldistributing (water) nozzles, assuming the same typical operating conditions as in Figure 8. The model predicts that for 3 maldistributing nozzles the NO_x would increase from 38.5 to 42.3 ppmvd. For 10 bad nozzles the NO_x emissions would increase ~30%, to ~ 55 ppmvd. Of course, there is no expectation that as all the nozzles fail or show excessive wear there will be an increase in water flow directed toward the wall. But it is reasonable to assume that malfunctioning nozzles will result in an increase in NO_x .

Figure 13: NO_x emissions versus number of maldistributing nozzles. Operating conditions given in Figure 8.

Example 2 – Predicting Malfunction Nozzles

Here we use data from Example 1, where emissions increased from 35 to 46 ppmvd over a 3 week period, and Figure 13 to predict the number of nozzles that may be malfunctioning. In Example 1 the key reconciled values fall within typical operating values (as reported in Figure 8) and these values were used in Figure 13. Figure 13 suggests the observed emissions increase may be caused by 6-7 damaged nozzles in the combustor. The cogeneration facility was shut down in late November, and inspected. It was found that 8 fuel nozzles were damaged and needed to be replaced (two of the nozzles are shown in Figure 10). Here we attributed the increased NO_x solely to the damaged injectors resulting in increased water flow towards the wall in the CRN. Other problems in the combustor, especially in the primary zone, can also result in increased NO_x .

4.3 Sensitivity of the On-Line Diagnostic Tool for Turbine System Problem Identification

While measured NO_x emissions can be used within the data reconciliation process to help identify system problems, it is also important to appreciate the limitations of any data reconciliation process.

Example 3 – Sensitivity of the Emissions Monitoring

Consider the same problem as Example 1, data from Table 1, except $NO_x = 42$ ppm (instead of 46 ppm). Data reconciliation indicates no gross errors, as $\chi^2_{(1-\alpha)}(v) = 6.102$ ($GT < \chi^2_{(1-\alpha)}(v)$), but Figure 13 suggests 3 bad nozzles are present. This exemplifies the difficulties associated with gross error detection through data reconciliation. An error is often smeared into the errors of other measured variables during data reconciliation (see [29] for further discussion). Variable threshold calculations [20] provide further insight into these difficulties. We calculate that the NO_x concentration would have to change by 12 ppm to ensure gross error detection 90% of the time.

Example 4 – Increase in Compressor Discharge Temperature

Finally we caution that simply observing NO_x values near 46 ppmvd as in Example 1 is not necessarily an indication of problems in the combustor. We performed data reconciliation with the measured variables of Table 1 and a measured $NO_x = 46$ ppmvd, except we biased the exit air temperature from the compressor (T_2) +36 R from its value in Table 1. Data reconciliation now results in $GT = 7.427$, so, as $GT < \chi^2_{(1-\alpha)}(v)$, gross errors are not detected. Increases in T_2 can also result in increased NO_x [59-63]. It is not possible to directly attribute an increase in T_2 to compressor fouling. However, as fouling also generally results in reductions in air flow, compressor discharge pressure and system net power, it is generally detectable.

5. Conclusions

Data reconciliation can be used to adjust measured data and help identify the onset of problems in a gas turbine-based cogeneration system. A CRN utilizing detailed kinetics modeling was combined with the measured NO_x in order to enhance the data reconciliation process. Measured NO_x emissions were related to the exit temperature of the combustor via a fast (curve fitted) NO_x model, which segmented into 15 regions the combustor's operating parameters. The inclusion of the NO_x emissions in data reconciliation allowed the detection of a wider range of system problems, especially within the combustor itself. To the author's knowledge this is the first reported use of NO_x emissions to enhance the data reconciliation process. Standard diagnostic tools including vibration monitoring, turbine temperature distribution and data reconciliation,

without utilizing measured NO_x , do not always show degradation in injector or combustor performance. However, the use of data reconciliation requires experience to pinpoint specific problem locations, and care in addressing well-known data reconciliation issues such as variable adjustability and error smearing.

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Appendix. Constants used in Equation (3) to determine adiabatic temperature in the combustor

Table A1: $T_3^{adiabatic} = A (NO_x)^a + B \left(\frac{fuel}{air} \right)^b + C (T_2)^c + D \left(\frac{water}{fuel} \right)^d + E (T_{Fuel})^e$ for GE LM-2000

$\frac{water}{fuel}$	$\frac{fuel}{air}$	A	a	B	b	C	c	D	d	E	e
0.8-1.0	0.0165-0.0180	1237.537	0.206	113.056	0.92	39.884	0.0011	-308.534	-1.324	0.558	0.01
	0.0180-0.0190	1289.061	0.192	104.665	1.2	53.218	0.0091	-266.311	-1.363	0.0358	0.01
	0.0190-0.0200	1224.984	0.198	104.33	2.22	51.447	0.0091	-158.729	-2.08	0.459	0.01
	0.0200-0.0210	1255.641	0.1935	106.22	1.22	51.347	0.0091	-156.926	-2.06	0.459	0.01
	0.0210-0.0220	1425.074	0.173	109.74	1.19	52.817	0.0099	-266.058	-1.22	0.5425	0.0048
1.0-1.2	0.0165-0.0180	1198.776	0.213	110.445	1.232	39.884	0.0011	-308.534	-1.324	0.558	0.01
	0.0180-0.0190	1327.824	0.19	95.422	1.09	54.109	0.0091	-325.379	-1.742	0.0358	0.01
	0.0190-0.0200	1277.161	0.196	106.73	1.255	52.379	0.0099	-250.136	-2.388	0.332	0.0099
	0.0200-0.0210	1296.965	0.1923	107.791	1.198	56.122	0.0099	-237.655	-2.48	0.2426	0.007
	0.0210-0.0220	1447.911	0.1741	109.996	1.124	56.123	0.011	-325.993	-1.53	0.6227	0.023
1.2-1.4	0.0165-0.0180	1269.109	0.1984	102.33	1.2	53.522	0.0091	-398.086	-3.359	0.0358	0.01
	0.0180-0.0190	1397.13	0.1835	101.254	2.229	54.098	0.01	-441.96	-1.994	0.0358	0.01
	0.0190-0.0200	1311.186	0.1924	107.234	2.22	53.596	0.091	-372.82	-3.405	0.4586	0.01
	0.0200-0.0210	1364.139	0.188	109.708	1.191	53.239	0.0099	-387.463	-2.713	0.5425	0.0048
	0.0210-0.0220	1538.626	0.167	102.48	1.338	57.477	0.011	-456.829	-1.53	0.2767	0.022

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