Mike Halpin

RTP ENVIRONMENTAL ASSOCIATES INC.®

AIR · WATER · SOLID WASTE CONSULTANTS

239 U.S. Highway 22 East
Green Brook, New Jersey 08812-1909
(www.rtpenv.com)

(732) 968-9600
Fax: (732) 968-9603

March 13, 2002

Mr. Al Linero
Florida Department of Environmental Protection
Bureau of Air Regulation
111 South Magnolia, Suite #4
Tallahassee, FL 32301

Re: Lee County Energy Recovery Facility – Unit 3

Dear Mr. Linero:

As requested by the Department and discussed at our meeting on December 13, 2001 (see attached), the Lee County project team has carefully reviewed the available emissions data from the existing two units at Lee County's Energy Recovery Facility. Although we still believe that the NSPS limits are stringent and protective standards, additional analyses have been performed in order to be responsive to FDEP's concerns. These analyses included both stack test data and continuous emissions monitoring data. These data were analyzed to determine appropriate permit limits for the proposed new unit. EPA's research for the New Source Performance Standard (NSPS) was also considered.

Attached are two copies of a report from Predictive Sciences, Inc. that details the statistical analyses that were utilized to determine upper predicted limits (UPL). As discussed with the Department, a "Six Sigma" approach was used in an attempt to develop appropriate upper limits. The report represents a rigorous mathematical approach to develop UPL's based on the available data from the facility – 7 years of annual tests plus continuous emission monitoring data. The Six Sigma UPL is a value that represents the limit that would not be exceeded 3.4 times per million events (approximately 125 years of operation). It is based upon statistical reliability theory, and represents the quantitative value such that the probability of compliance during any one hour sampling period exceeds 99.999%. It is worth noting that the final permit limits are deterministic (i.e., they represent never to exceed values), consistent with the Clean Air Act's permit requirements, which are never to exceed values. Therefore, as demonstrated by current facility testing, there is a high probability that the facility will remain in compliance.

After compiling and analyzing the data, the County's consultants and legal representatives worked to define permit limits that were acceptable to the vendor (operator) as well as the County. As can be noted in Table D-1, Page 5 in the report, UPL values less than the NSPS or existing permit limits are predicted for VOCs, fluorides (HF), cadmium (Cd) and lead (Pb). However, lead and cadmium pose particular problems because emissions (and control) of these pollutants are determined by the waste stream which is variable by nature. Further, the NSPS limits for these pollutants already are set very low. Note that there already is a 50% reduction in the emission limit for cadmium and a greater than 50% reduction in the lead limit from the existing units which are regulated under the Emission Guidelines and the NSPS for the new unit. Therefore, the county and vendor are unable to accept any reduction in the NSPS limits for these two pollutants due to the potential variability in the waste stream and the already low level required by the NSPS.

Based on the statistical study and other factors, Lee County is willing to accept permit limits for the third MWC unit that are lower than the NSPS values (or the existing permit level where no NSPS is specified) for four parameters: VOCs; HF; SO_2; and particulate matter. The attached table identifies the County's proposed emission factors for all pollutants. There are no NSPS limits for fluorides or VOCs because these are regulated as MWC acid gases and MWC organics. However, there are current permit limits for HF and VOCs in the Title V permit for the existing MWC units. The County is proposing an approximate 30% reduction in the limit for HF; an approximate 20% reduction in the VOC level; a 10% reduction in the PM level; and a 3% reduction in the SO_2 limit for the proposed new unit.

Considerable effort and expense was expended by the County, its consultants and the vendor in developing these proposed emission limits. This included a review of the Reference Methods, Accuracy And Precision (REMAP) studies performed by ASME concerning USEPA Methods 5, 23, 26 and 29, as well as a review of data from other Florida facilities. We feel that the proposed levels represent stringent yet achievable standards based on the performance of the existing units, and the extensive database compiled by USEPA in developing the New Source Performance Standards. The database of facility and emission control technologies that were utilized by USEPA to develop the New Source Performance Standards is still current. There has been no advancement in Best Available Control Technology that would allow the vendor and County to propose lower limits.

We would like to point out that while the statistical effort was rigorous and extensive, statistics by themselves are not adequate to determine an achievable emission limit. As noted above, professional judgement accrued through experience is necessary to determine whether an emission limit is achievable and is therefore appropriate for being enforceable. Achievable in the federal context of emission standards requires that the limit must be continuously achievable for known or expected variations in a process.

It should also be noted that the limit selected will have little effect on the design or operation of the facility. The facility will be designed to meet BACT requirements and the Maximum Achievable Control Technology requirements. Further, CEM data and test reports document that long term emissions are considerably less than the short term emissions factors that are monitored and regulated by continuous emission systems or short term stack tests.

We appreciate your consideration of these materials. Should you have any questions concerning the report or the proposed limits, please feel free to contact either Lindsey Sampson at 941-338-3302 or myself at the above number.

Sincerely,

RTP ENVIRONMENTAL ASSOCIATES, INC.®

Donald F. Elias

Donald F. Elias
Principal

DFE/lm

Att.

cc:	Howard Rhodes	B. Bahor
	Mike Halpin	J. Treshler
	L. Sampson	W. Corbin
	D. Dee	M. Hober
	S. Rosania	S. Heath
	J. Hahn	Project File: MPLC

Appropriate Permit Limits for Proposed Lee County Energy Recovery Facility (Unit 3)
December 13, 2001 (Revised)

At the request of the FDEP, the Lee County project team has reviewed the current plant operational data as well as test data from other facilities. The purpose of this effort is to determine appropriate permit limits for the proposed new unit for the Lee County Energy Recovery Facility. The starting point for the permit limits begins with the 1995 New Source Performance Standards. USEPA based the performance limits in the NSPS on the most recent available data. This included 12 units with spray dry absorbers, fabric filters and selective non-catalytic reduction systems operating in 1994, as well as earlier data. Overall, EPA used performance test data from over 60 municipal waste combustor plants (60 FR 65391, 19 December 1995 and 60 FR 65396, 19 December 1995). As required by Congress, the NSPS "MACT Floor" is set at the level achieved by the best performing plant. Although EPA did not include European test data, it did indicate that the European data would not have changed the limits (59 FR 48254, 20 September 1994, Section VII - *Comparison of the Proposal and European Emission Limits*).

Due to the United States Supreme Court "Carbone" ruling on May 16, 1994, (1994 WL 183594 (U.S.N.Y.)), little development of new MWCs has occurred in the United States after 1994. Hence, the conclusions reached by USEPA at that time should still be valid. There has been some additional experience gained in the operation of facilities equipped with modern pollution control trains, including spray dry absorbers, fabric filters, selective non-catalytic reduction systems and activated carbon injection systems. Enhanced combustion controls have also improved overall municipal waste combustor performance (good combustion practice). The only potential modifications to these designs for a new facility could be the use of a selective catalytic reduction (SCR) system for NO_x control. These systems began being applied to municipal waste combustors in Europe and Asia in the early 90's and were reviewed by USEPA in setting the NSPS. They will be reviewed further, based on current costs, in the BACT review for this project.

Therefore, based on the BACT considerations, this facility will be designed and operated in accordance with the NSPS standards. <u>Regardless of the permit limits, there will be no change in the basic design or operation of the proposed facility</u>, unless SCR is added for NO_x control. The operation of the combustor, as well as the pollution control train, is continuously monitored and strictly regulated. The steam load is tied to the most recent dioxin stack tests demonstrating compliance with the applicable limit. The municipal waste combustor load cannot exceed more than 110% of the rate achieved during the last approved stack test. This effectively limits the load to the combustor. Additionally, the inlet temperature to the bag house is monitored to ensure that condensed metals are collected and dioxins are not formed on the particulate in the bag house. The maximum temperature cannot be more than 17°C (30.6°F) above the temperature measured during the last approved dioxin stack tests. In addition, there are continuous emission monitors for SO_2, at the inlet of the spray dry absorber and at the stack. SO_2 is one of the more difficult acid gas species to remove and control of SO_2 to the NSPS limits indicates sufficient control of HF and HCl. The combustion related conditions are monitored continuously through CO and NO_x continuous emission monitors, along with the automatic combustion control system, to ensure proper combustion control. There are also opacity and pressure drop monitors that ensure proper performance of the bag house. These instruments are monitored by control room personnel to ensure the proper operation of the facility. There is a monitoring requirement for the carbon feed rate to ensure adequate control for mercury and other volatile metals. The accuracy of the pollution monitors are verified by quarterly performance specification tests. Those regulated pollutants not monitored by continuous emission monitors are typically subject to periodic stack tests. The overall effect of the design, control, and monitoring systems is to ensure that the operation of the plant is subject to continuous agency oversight and hence fully protective of the public and the environment.

As noted above, regardless of the emission limit set in the permits, there will be no difference in the design or operation of the facility, unless SCR is required. Overly stringent permit limits merely increase the risk of spurious "exceedences" of an overly-restrictive standard. (Note: Economic analysis of the inclusion of an SCR $DeNO_x$ system for the proposed unit indicates the project can not be recommended by the County's Solid Waste Division)

It should be noted that the metals emissions are not guaranteed by the vendor and are the responsibility of the County. The County has maintained an aggressive materials separation/recycling program as outlined in the Materials Separation Plan for this project. There is a limited ability to predict what the variability of the waste stream will be over the life of the facility and life of the permit. The permit limits must be set to accommodate the full range of variability that may occur in the waste stream over this time. In order to provide reasonable assurance that a lower limit could be met for the NSPS metals (cadmium, lead, mercury) additional control equipment would be required, likely including a wet ESP. Costs for such additional control would be prohibitive, both on a cost per ton removed and the effect it would have on the tipping fee for the facility.

Due to the limited amount of test data available for the stack test pollutants (21 data points), there is some difficulty in determining what, if any, reductions can be achieved in practice to allow lower permit emission limits than the NSPS. Since the permit limits are deterministic, pass/fail limits that can never be exceeded, it is appropriate that they accommodate the full range of normal operation. Therefore, historical operating data supports the use of the NSPS limits as aggressive, appropriate permit limits.

Predictive Sciences

Statistical Determination of Upper Prediction Limits for Constituent Distributions

*A project study for **RTP Environmental Associates, Inc.***

Predictive Sciences International
30 East Brown Road, Suite 2076, Mesa, AZ 85201
www.predictivesciences.com *480.655.0015*

Statistical Determination of Upper Prediction Limits for Constituent Distributions

Executive Summary

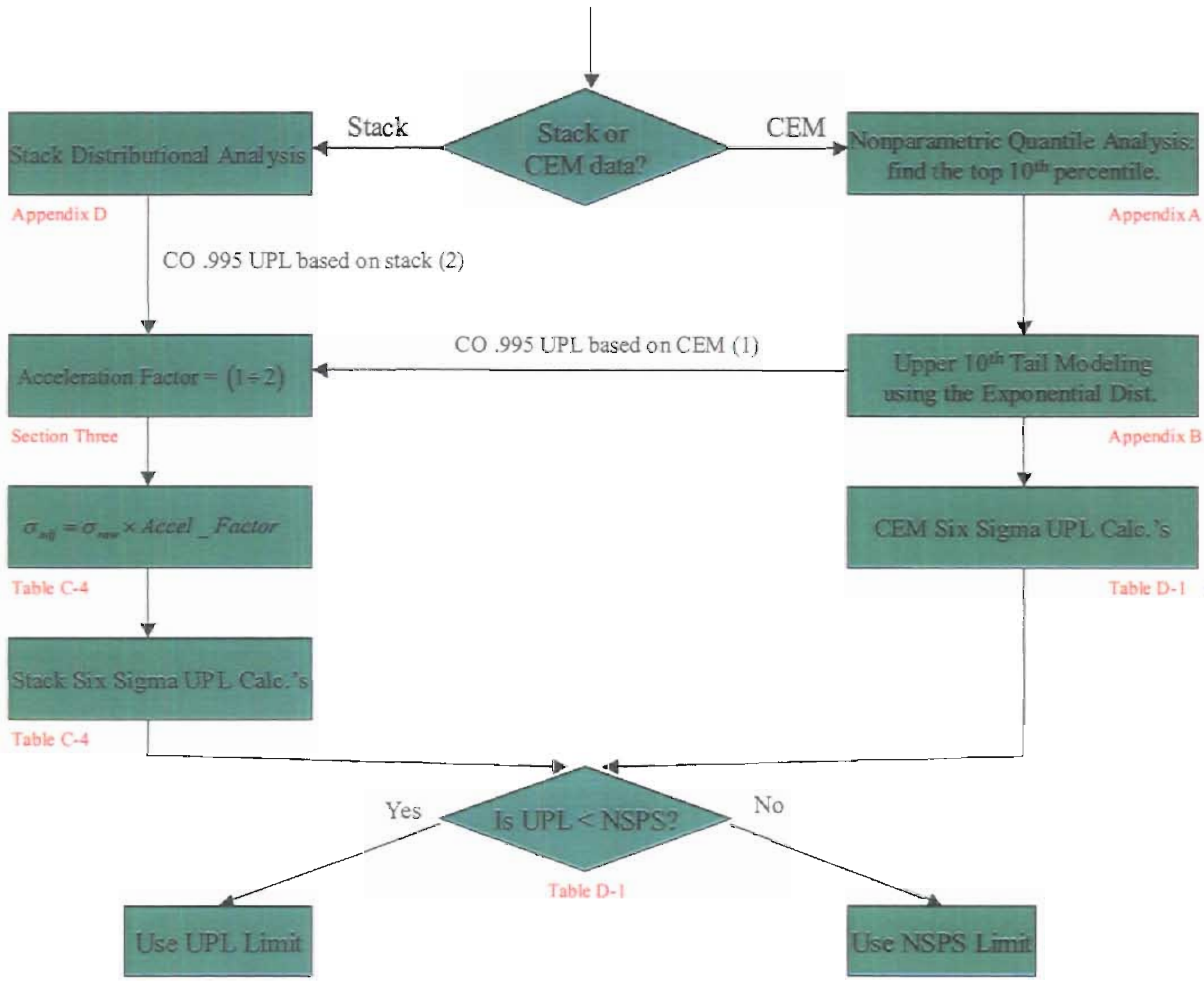
The objective of this project is to statistically derive **Upper Prediction Limits** (UPL's, as discussed in Appendix D) relative to sampling distributions of 12 constituent variables. The data are associated with a Prevention of Significant Deterioration (PSD) permitting process for the Lee County Energy Recovery Facility in the southeastern United States. Knowledge of the applicable UPL's from existing operations is beneficial in the determination of appropriate values for permit levels in future operations.

While the statistical effort was rigorous and extensive, statistics by themselves are not adequate to determine an achievable emission limit. Professional judgment accrued through experience is necessary to determine whether an emission limit is achievable, and is therefore appropriate for being enforceable. Achievable in the federal context of emission standards requires that the limit must be continuously achievable for known or expected variations in a process.

Historical operations data exists in two forms. ***Stack*** data is measured once per year as 3 repeated measures, and is available across 7 years for all 12 variables. ***CEM*** data (continuous emission monitoring) is reported as either a 4-hour average (for CO) or a 24-hour average (for SO_2 and NO_x); CEM data is available for 3 variables continuously across 19 months. It is desired to set the UPL such that it represents a 3.4 parts per million level, the ***Six Sigma*** value. Six Sigma quality and reliability theory has been widely studied and applied throughout industry to provide high reliability tolerancing for a variety of complex systems.

Executive Summary (cont).

This Six Sigma (6σ) Upper Prediction Limit requires careful statistical estimation. An overview of the modeling and analysis strategy follows as Flowchart A. Each major segment of the analysis sequence is detailed in its referenced appendix. Final Results are shown on Table D-1 following Flowchart A, and are presented in detail in Appendix D. The Six Sigma UPL is a quantitative level such that, for any hour of operation, the probability that the facility emissions are above the UPL is 3.4 in a million. The Six Sigma UPL is an estimated numerical value based on an analysis of site data. The UPL is not a known value that emanates directly from actual facility operations. Compliance test results and compliance reports should be researched for actual operating data at the facility and for a comparison with facility permit limits.



FLOWCHART A: Analysis and Modeling Strategy

STACK				
Constituent	units	Six Sigma UPL	NSPS limit	Appl_Lim
VOC/NMHC (1)	ppmdv@7%O_2	30.43	37.00	Six Sigma UPL
HF (1)	ppmdv@7%O_2	1.053	5.000	Six Sigma UPL
Be(1)	mcg/dscm@7%O_2	0.0007873	0.0001590	NSPS limit
Cd	mg/dscm@7%O_2	0.01249	0.02000	Six Sigma UPL
Pb	mcg/dscm@7%O_2	0.1135	0.2000	Six Sigma UPL
PM	gr/dscf@7%O_2	0.01802	0.01000	NSPS limit
Hg	mcg/dscm@7%O_2	289.4	70.00	NSPS limit
HCl	ppmdv@7%O_2	190.5	25.00	NSPS limit
Total PCDD/F	ng/dscm@7%O_2	177.7	13.00	NSPS limit
CEM				
Constituent	units	Six Sigma UPL	NSPS limit	Appl_Lim
NOx	ppmdv@7%O2	262.4	150.0	NSPS limit
SO2	ppmdv@7%O2	31.68	29.00	NSPS limit
CO	ppmdv@7%O2	150.8	100.0	NSPS limit

(1) VOC, HF, Be: No NSPS standard, PSD limit from existing Units 1& 2
Permit limit for NH3 not addressed as no operational history for 150 ppmdv NOx limit
Note: The emission limits presented above do not include the removal efficiency standard provided by 40 CFR Part 60, subpart Eb or the time-weighted averages for pollutants requiring continuous monitoring. The removal efficiency is 85% for Hg, 80% for SO2, and 95% for HCl.

TABLE D-1: Six Sigma UPL v. NSPS Limits.

Section One: Overview

As discussed in the Executive Summary, the project objective is determination of Upper Prediction Limits (UPL's) on 12 variables. All 12 variables have stack test data across 7 years (3 repeated measurements per year), while 3 of the 12 variables additionally have CEM (continuous emission monitoring) data comprised of 4-hour or 24-hour averages reported continuously across a 19-month period.

The CEM data (representing CO, SO_2, and NO_x) support statistical estimation of the Six Sigma UPL through a two-stage nonlinear modeling process (Appendices B and C). In contrast, the statistical *sparcity* of the stack data precludes direct parametric estimation of the Six Sigma UPL. Subsequently, acceleration factors are estimated through parametric modeling of the upper tail probability density function (Section Three). These models permit the observable stack parameters to be mapped into predicted CEM parameters, which in turn support estimation of the Six Sigma UPL's for the stack variables.

Section Two: CEM Exploratory Data Analysis and UPL Calculation

The following pages describe observed histograms of the 3 CEM variables (Graph A-1), along with many important distributional indices. The SO_2 and NO_x constituents are based upon 24-hour averaging, which results in distributions with pronounced central tendencies. The SO_2 and NO_x skewness statistics (-0.0158 and –0.393 respectively) are both relatively close to zero, indicating that the distributions are symmetric (skewness is defined as the third moment about the mean). The kurtosis statistics however strongly suggest that these 2 distributions are *composite* distributions that likely emanate from an unknown set of *multimodal* processes. This assumption is consistent with our knowledge of RRF operations, in which feed stock, environmental, facility, and numerous other perturbing factors affect daily operations.

Graph A-1 displays several Exploratory Data Analysis tools, which we will describe briefly.

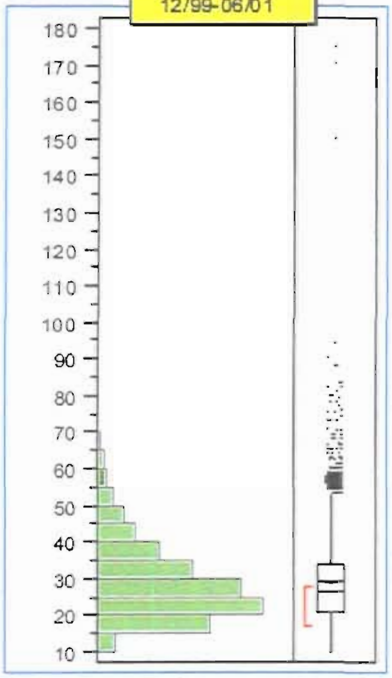
"Histogram: Each bar shows the frequency of occurrence of the value or range of values represented on the axis. If the variable is continuous, the axis is broken into intervals. If the variable is nominal, each discrete value is represented by a bar. The Y-axis represents the variable value (for CEM data, it is ppmdv@7%O2), and the x-axis represents relative frequency.

The Box and Whiskers Plot is a schematic that lets you see the sample. The ends of the box are the 25th and 75th quantiles, also called the quartiles. The difference between the quartiles is the interquartile range. The line across the middle identifies the median sample value. The ends of the whiskers are the outer-most data points from their respective quartiles that fall within the distance computed as 1.5 *(interquartile range). The bracket along the edge of the box identifies the shortest half, which is the most dense 50% of the observations. Quantiles are values that divide a distribution into two groups where the Pth quantile is larger than P% of the values. For example, half the data are below and half the data are above or equal to the 50th quantile, also called the median."

The distribution of the CO constituent is markedly different from the distributions of the other 2 CEM variables. It is noted that CO is recorded as a 4-hour average value (versus a 24-hour average value), and accordingly has a gauging frequency 6 times greater than either SO_2 or NO_x.

The CO constituent distribution is positively skewed; its skewness coefficient of 2.523 is indicative of an asymmetric distribution. The once per year stack test (3 sequential measurements taken in the same day) is roughly equivalent gauging frequency to the CO CEM 4-hour average sampling plan, and accordingly the CO CEM data is used in the determination of the acceleration factors required for stack Six Sigma UPL estimation (Section Three).

COec_4h



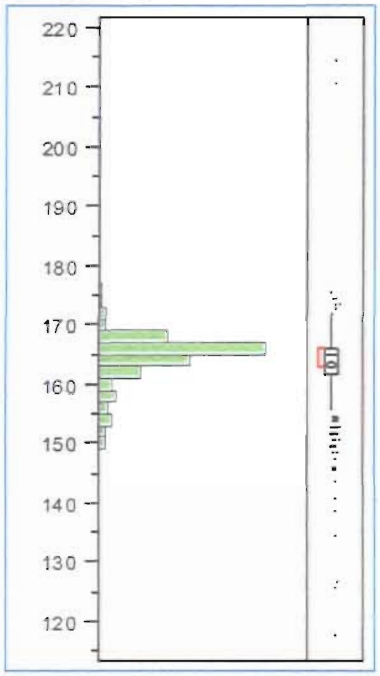
Quantiles

maximum	100.0%	176.00
	99.5%	80.78
	97.5%	61.00
	90.0%	45.00
quartile	75.0%	34.00
median	50.0%	27.00
quartile	25.0%	21.00
	10.0%	17.00
	2.5%	14.08
	0.5%	13.00
minimum	0.0%	10.00

Moments

Mean	29.361
Std Dev	12.530
Std Error Mean	0.227
Upper 95% Mean	29.806
Lower 95% Mean	28.915
N	3042.000
Sum Weights	3042.000
Sum	89315.000
Variance	157.012
Skewness	2.523
Kurtosis	16.216
CV	42.678

NOXsc_24h



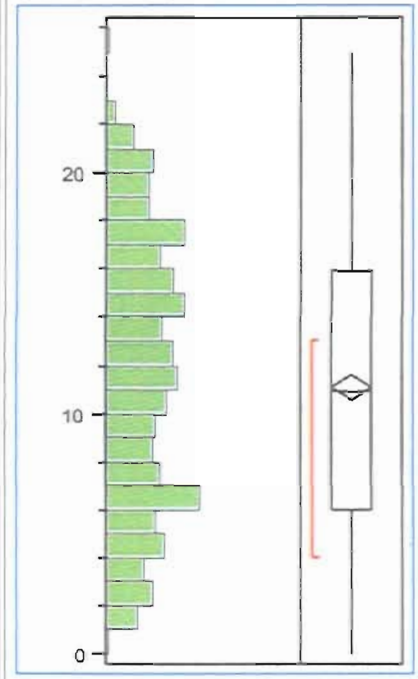
Quantiles

maximum	100.0%	215.00
	99.5%	192.63
	97.5%	171.00
	90.0%	167.00
quartile	75.0%	166.00
median	50.0%	165.00
quartile	25.0%	162.00
	10.0%	155.50
	2.5%	149.00
	0.5%	126.52
minimum	0.0%	118.00

Moments

Mean	163.3750
Std Dev	6.6989
Std Error Mean	0.2984
Upper 95% Mean	163.9613
Lower 95% Mean	162.7887
N	504.0000
Sum Weights	504.0000
Sum	82341
Variance	44.8750
Skewness	-0.3930
Kurtosis	19.6607
CV	4.1003

SO2sc_24hg



Quantiles

maximum	100.0%	25.000
	99.5%	22.000
	97.5%	21.000
	90.0%	19.000
quartile	75.0%	16.000
median	50.0%	11.000
quartile	25.0%	6.000
	10.0%	3.000
	2.5%	1.000
	0.5%	1.000
minimum	0.0%	0.000

Moments

Mean	11.1361
Std Dev	5.6582
Std Error Mean	0.2513
Upper 95% Mean	11.6298
Lower 95% Mean	10.6424
N	507.0000
Sum Weights	507.0000
Sum	5646.0000
Variance	32.0150
Skewness	-0.0158
Kurtosis	-1.0369
CV	50.8094

GRAPH A-1: CEM Variables Distributional Analysis

Focus will now be directed upon the Six Sigma UPL calculation for the 3 CEM variables. Given that the 3 variables all appear to emanate from multimodal distributions (as evidenced by the skewness and kurtosis statistics), it is logical to turn to *nonparametric* approaches; i.e., approaches that do not rely upon distributional assumptions. One such technique is quantile analysis, in which a dataset is rank ordered and quantiles estimated. For example, consider the 90.0% quantile listed for each variable on Graph A-1. This value is such that only 10% of the observed values in the sample distribution were greater in value; in other words, it represents the 10% upper tail of the distribution (regardless of the true, unknown distributional form)

Robust estimation of the upper tail areas of each variable's distribution is important. Many things are happening in the parent distribution, but we are only concerned about those phenomenological events that generate the most extreme realizations; these events are represented by the upper tail areas uniquely. Our strategy will be to identify in a nonparametric fashion the upper 10th percentile of each distribution (as shown in Graph B-1). Given that these upper tails are smooth monotonic functions that sufficiently represent the phenomena of interest, it is then proposed that we model these curves using the exponential function to provide extrapolation estimates of the Six Sigma UPL's.

The exponential function is represented as:

$$y_t = \beta_1 e^{\beta_2 x_t}.$$

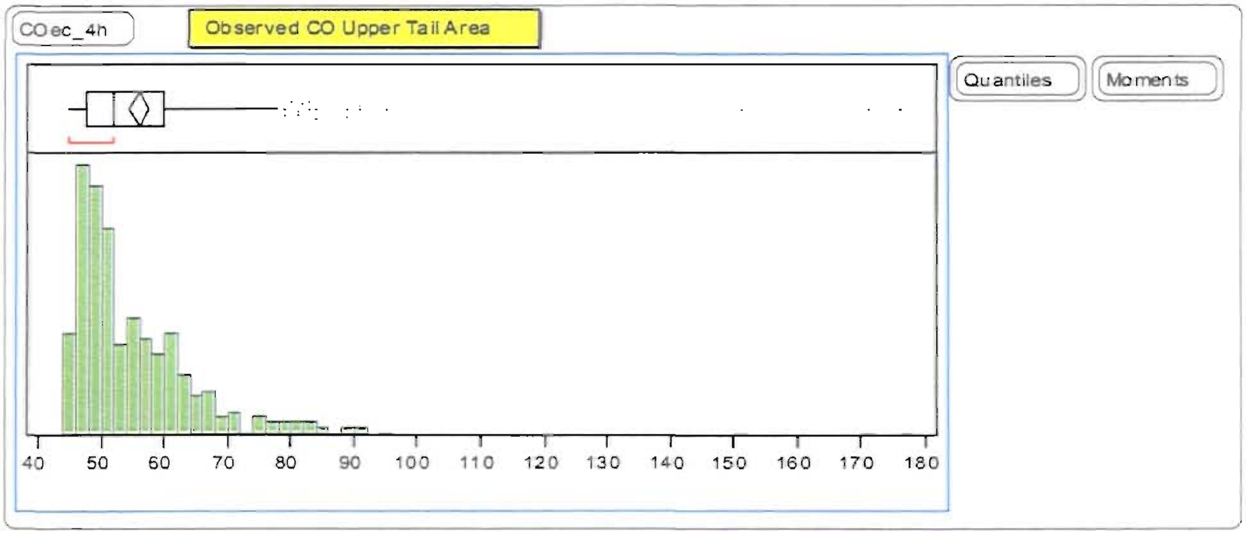
Through different values of β_1 and β_2, the exponential curve can demonstrate significant flexibility in modeling nonlinear, monotonic, asymptotic functions (as demonstrated in Graph B-2). Exponential decay is a very popular model in engineering and physical sciences, and has been used successfully in many modeling projects. The exponential function is *parsimonious*, meaning that only two parameters require statistical estimation. Parsimony is a highly desirable property in statistical modeling, as it minimizes the potential for in-sample overfit and resulting reduction in out-of-sample predictive capability. Lastly, the exponential distribution is the least restrictive of all statistical distributions; as some distributional assumptions must be made to generate probability estimates in the extreme tail areas, it seems logical to utilize the least restrictive assumption set as possible.

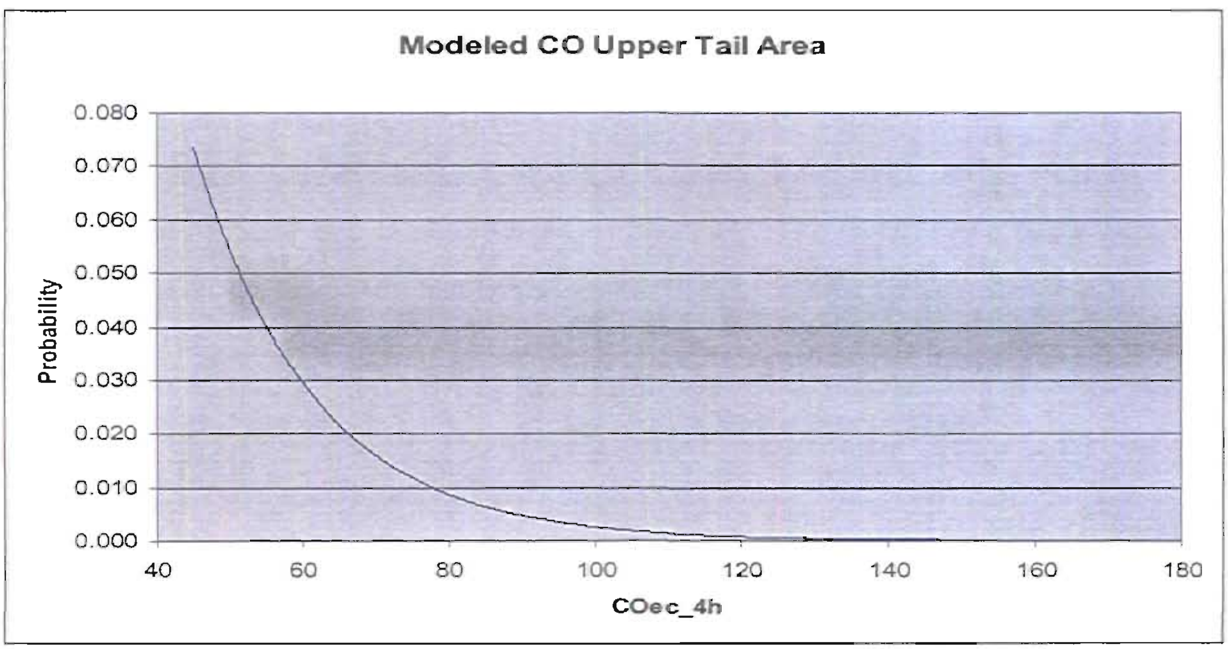
The exponential function has the additional benefit of being *intrinsically linear*; i.e., that through a transcendental transformation (natural log in this case), the strictly nonlinear exponential function may be linearized to facilitate computational solution, as follows:

$$\ln y_t = \ln\left(\beta_1 e^{\beta_2 x_t}\right)$$

$$\ln y_t = \ln(\beta_1) + \beta_2 x_t .$$

This transformation permits β_1 and β_2 to be estimated with Ordinary Least Squares (OLS) linear regression. A separate exponential model was fit to the upper tail area of each CEM variable, with full details reported in Appendix B. Once the upper tail models are parameterized (as summarized in Tables B-3, 4, &5), it is straightforward to estimate the Six Sigma UPL (this would be equivalent to 3.4 ppm = .0000034). This probability point is substituted for y_t in the applicable exponential model, and the corresponding constituent value x_t (the Six Sigma UPL) can be solved for directly (results presented in Table D-1). The following page shows results for CO; see Appendix B for complete results.





GRAPHS B-6 & B-7: Observed CO Upper Tail Area and Modeled CO Upper Tail Area
Note that the modeled distributions have been normalized such that area under the curve is equal to 0.1000, in accordance with these upper tail areas representing the ten percentile of the parent distribution.

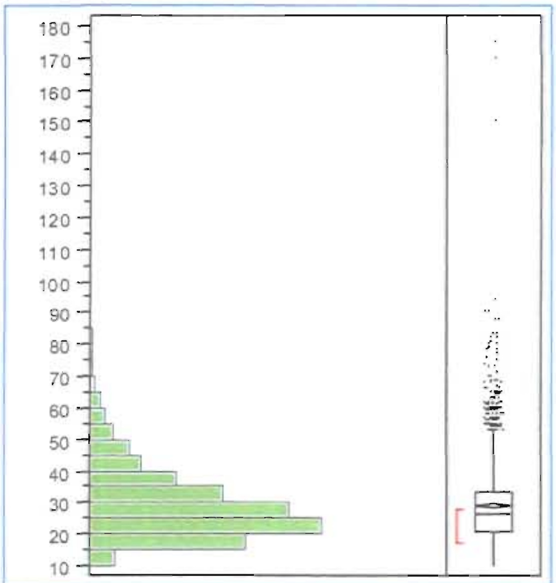
Section Three: Stack Acceleration Factors

In the stack tests, 3 measurements are taken sequentially within the shortest time period possible, and represent the base level *component of variance*. This component encompasses instantaneous gauge repeatability (including gauge bias and linearity effects), as well as the short-term component of process variability. In this project, these two components are statistically confounded and may only be estimated jointly. Decomposition of this confounded component into its base components could be conducted building upon prior research summarized in the recent ASME report "Precision of Manual Stack Measurements" (*Reference Method Accuracy and Precision*, CRTD Vol. 60, American Society of Mechanical Engineers, February 2001). The ASME project quantified instantaneous gauge repeatability of stack metrology utilizing specialized multi-train gauge clusters. Typically, stack measurements are taken with a single train gauge, where confounding of the type we are experiencing is typical.

In this study, the once-per-year stack readings are available for from 4 to 7 years, depending upon the variable. At best, a maximum of 21 readings will be available, compared to over 3000 for the CO Continuous Emission Monitoring (CEM) data. Given that the CO CEM reading is a 4-hour arithmetic average, it would have a gauge frequency roughly similar to the 3 readings per day approach of the yearly stack tests. It is proposed that by comparing the distributional properties between the CO stack test and the CO CEM data, acceleration factors may be estimated that could statistically map stack distributional properties into CEM distributional properties. Upper Prediction Limits (UPL's) consistent with the Six Sigma level could then by estimated for stack constituents in addition to the large CEM data variables.

Consider the observed distributions of CO for the CEM and the stack data, as shown on the next page in Graph C-1:

COec_4h



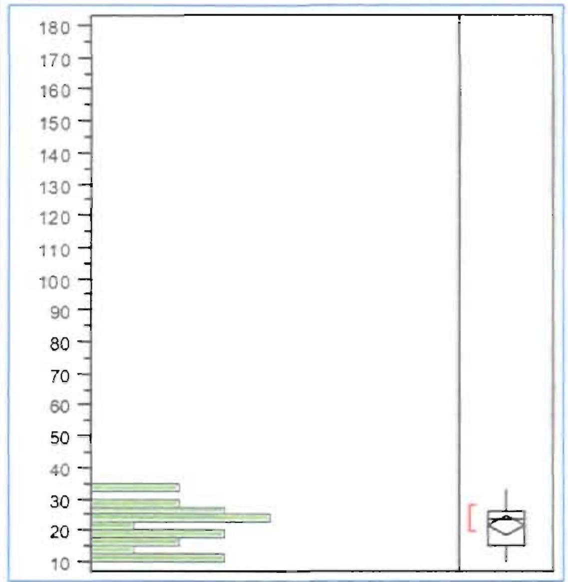
Quantiles

maximum	100.0%	176.00
	99.5%	80.78
	97.5%	61.00
	90.0%	45.00
quartile	75.0%	34.00
median	50.0%	27.00
quartile	25.0%	21.00
	10.0%	17.00
	2.5%	14.08
	0.5%	13.00
minimum	0.0%	10.00

Moments

Mean	29.361
Std Dev	12.530
Std Error Mean	0.227
Upper 95% Mean	29.806
Lower 95% Mean	28.915
N	3042.000
Sum Weights	3042.000
Sum	89315.000
Variance	157.012
Skewness	2.523
Kurtosis	16.216
CV	42.678

CO_stack



Quantiles

maximum	100.0%	33.100
	99.5%	33.100
	97.5%	33.100
	90.0%	32.120
quartile	75.0%	26.300
median	50.0%	24.000
quartile	25.0%	15.250
	10.0%	11.660
	2.5%	10.600
	0.5%	10.600
minimum	0.0%	10.600

Moments

Mean	21.60476
Std Dev	6.81986
Std Error Mean	1.48822
Upper 95% Mean	24.70910
Lower 95% Mean	18.50042
N	21.00000
Sum Weights	21.00000
Sum	453.70000
Variance	46.51048
Skewness	-0.07860
Kurtosis	-0.97873
CV	31.56646

GRAPH C-1: Observed Distributions of CO: CEM (left) v. Stack (right)

CO	stack	CEM
n	21	3042
average	21.61	29.36
standard deviation	6.820	12.53
99.5%UPL	33.10	80.78
Max_Obsrved	33.10	176.0

TABLE C-2: Comparison of Distributional Properties – CO Stack v. CEM

As evident in both the histograms and the comparison Table C-2, the small sample stack data significantly underestimate the true variability associated with the constituent distribution. A more precise estimate of higher tail probabilities for CO may be introduced resulting from the upper tail exponential modeling work outlined in Section Two of this report. These values are summarized in Table C-3 below:

CO	**stack**	**CEM**	**CEM Model**
n	21	3042	3042/321
average	21.61	29.36	na
standard deviation	6.820	12.53	na
99.5%UPL	33.10	**80.78**	**88.96**
Max_Obsrved	33.10	176.0	176.0

TABLE C-3: Comparison of Distributional Properties – CO Stack v. CEM v. CEM Model

Recall from Section Two that the Upper 10th Percentile Tail Area of CO was modeled as an exponential function in order to obtain high-resolution probability estimation required for estimation of the Six Sigma UPL (a 3.4 ppm value). It is reassuring to see in Table C-3 that the 99.5% UPL from the CEM data and its corresponding estimate from the CEM model agree quite closely, indicating that the exponential function provides good predictive capability for CO upper tail probabilities.

Comparison of the 99.5% UPL between the CO CEM Model and the 99.5% UPL from the CO Stack data provide the basis for the estimation of the stack acceleration factor:

$$\text{Stack Acceleration Factor} = \frac{\text{99.5\% UPL CO CEM Model}}{\text{99.5\% UPL CO Stack Data}}$$

$$\text{Stack Acceleration Factor} = \frac{88.96}{33.10} = 2.688$$

This stack acceleration factor will be applied to adjust the stack standard deviations prior to making the Six Sigma UPL calculations, as follows:

$$\sigma_{adj} = \sigma_{raw} \times \text{ stack acceleration factor .}$$

Nine constituents have stack readings but no CEM readings. Table C-4 summarizes the stack constituents' sample averages, sample standard deviations, and sample sizes. It applies the acceleration factor to the raw stack standard deviation, and determines the Six Sigma UPL accordingly by constituent.

						Six Sigma:	3.4 ppm =	3.400E-06
Constituent	**units**	**n**	**Avg Stack Test**	**SD Stack Test**	**Accel.Factor**	**SD adj**	**t-value**	**Six Sigma UPL**
			D	E	F	G=(ExF)	0.0000034	(D + (GxH))
VOC/NMHC (1)	ppmdv@7%O2	18	1.764	1.539	2.688	4.138	6.929	30.43
HF (1)	ppmdv@7%O2	18	0.09702	0.05133	2.688	0.1380	6.929	1.053
Be(1)	mcg/dscm@7%O2	15	0.00005713	0.00003506	2.688	0.00009423	7.749	0.0007873
Cd	mcg/dscm@7%O2	12	0.0009106	0.0004663	2.688	0.001254	9.239	0.01249
PM	gr/dscf@7%O2	21	0.001464	0.0009501	2.688	0.002554	6.482	0.01802
Hg	mcg/dscm@7%O2	21	31.70	14.79	2.688	39.76	6.482	289.4
HCl	ppmdv@7%O2	21	21.90	9.679	2.688	26.02	6.482	190.5
Total PCDD/F	ng/dscm@7%O2	21	9.871	9.631	2.688	25.89	6.482	177.7
Pb	mcg/dscm@7%O2	21	0.006277	0.006152	2.688	0.01654	6.482	0.1135

(1) VOC, HF, Be: No NSPS standard, PSD limit from existing Units 1& 2
Permit limit for NH3 not addressed as no operational history for 150 ppmdv NOx limit
Note: The emission limits presented above do not include the removal efficiency standard provided by 40 CFR Part 60, subpart Eb or the time-weighted averages for pollutants requiring continuous monitoring. The removal efficiency is 85% for Hg, 80% for SO2, and 95% for HCl.

TABLE C-4: Stack Constituents and Six Sigma UPL Calculation

Columns C, D, and E are calculated directly from the Stack test data for each constituent.

Column F is the stack acceleration factor calculated in Section Three.

Column G is the product adjusts the sample standard deviation applying the accel factor.

Column H is the t-value associated with the small sample and the Six Sigma (.0000034) probability level.

Column I is the calculated Six Sigma UPL based upon the adjusted standard deviation.

Table D-1 compares the Six Sigma UPL to the NSPS limit.

STACK				
Constituent	units	Six Sigma UPL	NSPS limit	Appl_Lim
VOC/NMHC (1)	ppmdv@7%O_2	30.43	37.00	Six Sigma UPL
HF (1)	ppmdv@7%O_2	1.053	5.000	Six Sigma UPL
Be(1)	mcg/dscm@7%O_2	0.0007873	0.0001590	NSPS limit
Cd	mg/dscm@7%O_2	0.01249	0.02000	Six Sigma UPL
Pb	mcg/dscm@7%O_2	0.1135	0.2000	Six Sigma UPL
PM	gr/dscf@7%O_2	0.01802	0.01000	NSPS limit
Hg	mcg/dscm@7%O_2	289.4	70.00	NSPS limit
HCl	ppmdv@7%O_2	190.5	25.00	NSPS limit
Total PCDD/F	ng/dscm@7%O_2	177.7	13.00	NSPS limit
CEM				
Constituent	units	Six Sigma UPL	NSPS limit	Appl_Lim
NOx	ppmdv@7%O2	262.4	150.0	NSPS limit
SO2	ppmdv@7%O2	31.68	29.00	NSPS limit
CO	ppmdv@7%O2	150.8	100.0	NSPS limit

(1) VOC, HF, Be: No NSPS standard, PSD limit from existing Units 1& 2
Permit limit for NH3 not addressed as no operational history for 150 ppmdv NOx limit
Note: The emission limits presented above do not include the removal efficiency standard provided by 40 CFR Part 60, subpart Eb or the time-weighted averages for pollutants requiring continuous monitoring. The removal efficiency is 85% for Hg, 80% for SO2, and 95% for HCl.

TABLE D-1: Six Sigma UPL v. NSPS Limits.

Section Four: Summary

A scientific method for determining Upper Prediction Limits has been presented based on available data from the operation of the existing facility. The resulting UPL's have been generated in a statistically sound fashion and represent potential limits for future operations.

The Six Sigma UPL is an estimated numerical value based on an analysis of site data. The UPL is not a known value that emanates directly from actual facility operations. Compliance test results and compliance reports should be researched for actual operating data at the facility and for a comparison with facility permit limits.

Appendix A:

Nonparametric Quantile Analysis and Exploratory Data Analysis of CEM variables

GRAPH A-1: CEM Distributional Analysis

GRAPH A-2: COec_4h CEM Distributional Analysis

GRAPH A-3: COec_4h Chronological Time Series Plot

GRAPH A-4: Graphical Representation of CO Autocorrelation

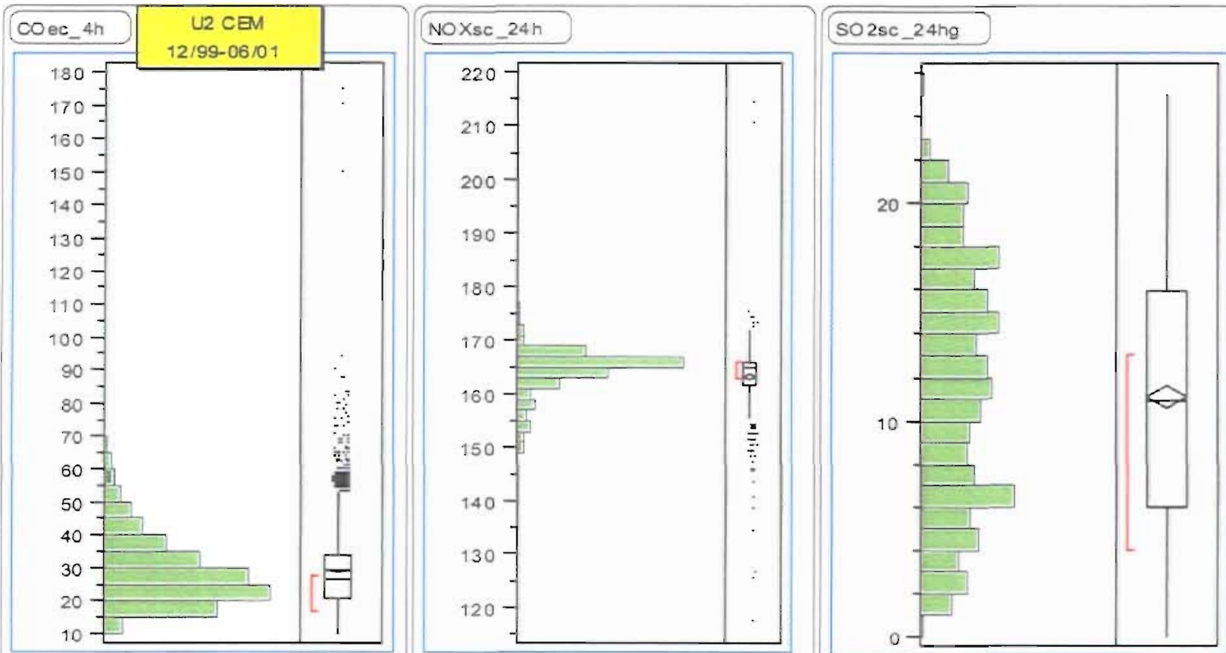
TABLE A-5: Regression Representation of CO Lag 1 Autocorrelation

GRAPH A-6: NO_xsc_24h CEM Distributional Analysis

GRAPH A-7: NO_xsc_24h Chronological Time Series Plot

GRAPH A-8: SO_2sc_24h CEM Distributional Analysis

GRAPH A-9: SO_2sc_24h Chronological Time Series Plot



COec_4h

Quantiles

maximum	100.0%	176.00
	99.5%	80.78
	97.5%	61.00
	90.0%	45.00
quartile	75.0%	34.00
median	50.0%	27.00
quartile	25.0%	21.00
	10.0%	17.00
	2.5%	14.08
	0.5%	13.00
minimum	0.0%	10.00

Moments

Mean	29.361
Std Dev	12.530
Std Error Mean	0.227
Upper 95% Mean	29.806
Lower 95% Mean	28.915
N	3042.000
Sum Weights	3042.000
Sum	89315.000
Variance	157.012
Skewness	2.523
Kurtosis	16.216
CV	42.678

NOXsc_24h

Quantiles

maximum	100.0%	215.00
	99.5%	192.63
	97.5%	171.00
	90.0%	167.00
quartile	75.0%	166.00
median	50.0%	165.00
quartile	25.0%	162.00
	10.0%	155.50
	2.5%	149.00
	0.5%	126.52
minimum	0.0%	118.00

Moments

Mean	163.3750
Std Dev	6.6989
Std Error Mean	0.2984
Upper 95% Mean	163.9613
Lower 95% Mean	162.7887
N	504.0000
Sum Weights	504.0000
Sum	82341
Variance	44.8750
Skewness	-0.3930
Kurtosis	19.6607
CV	4.1003

SO2sc_24hg

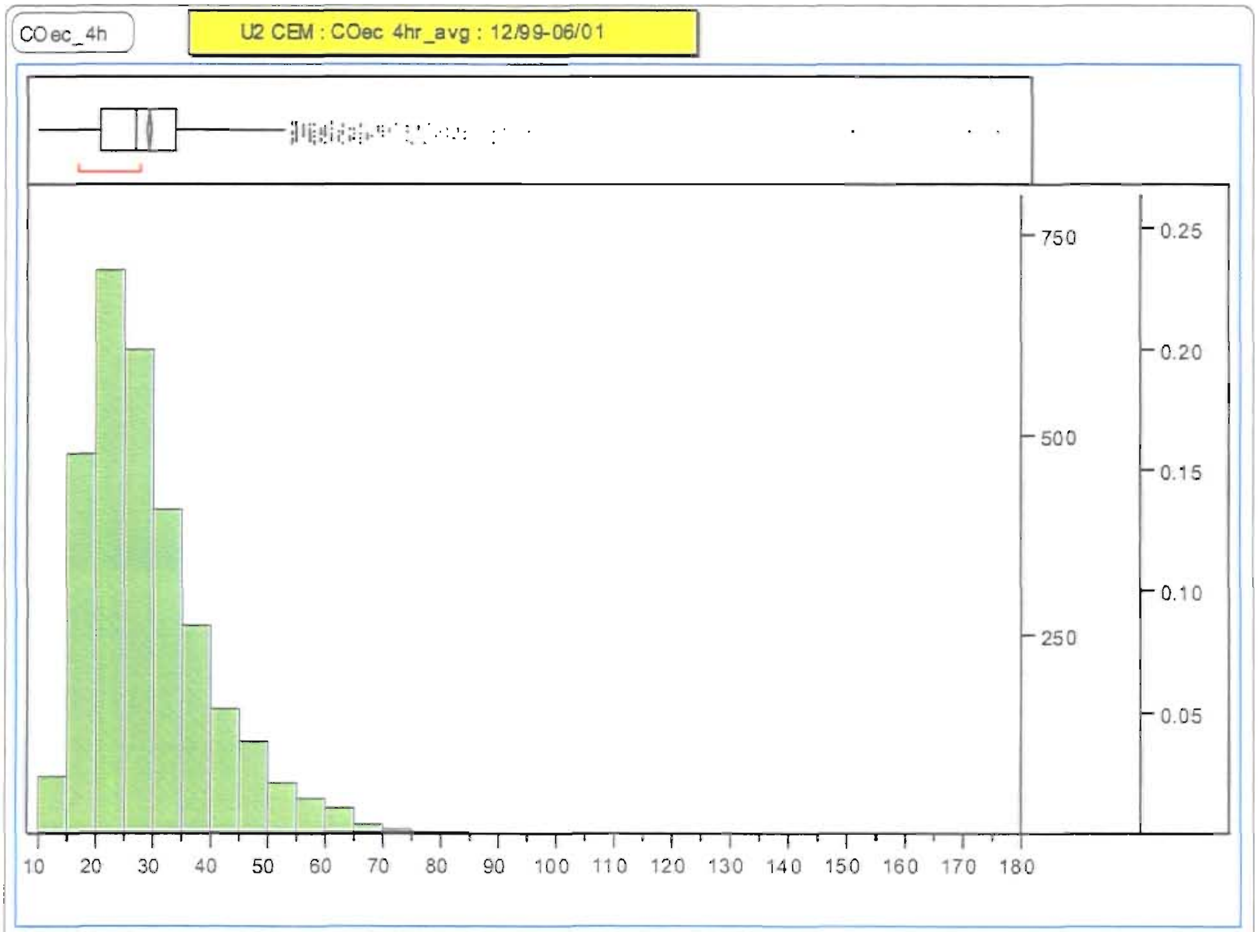
Quantiles

maximum	100.0%	25.000
	99.5%	22.000
	97.5%	21.000
	90.0%	19.000
quartile	75.0%	16.000
median	50.0%	11.000
quartile	25.0%	6.000
	10.0%	3.000
	2.5%	1.000
	0.5%	1.000
minimum	0.0%	0.000

Moments

Mean	11.1361
Std Dev	5.6582
Std Error Mean	0.2513
Upper 95% Mean	11.6298
Lower 95% Mean	10.6424
N	507.0000
Sum Weights	507.0000
Sum	5646.0000
Variance	32.0150
Skewness	-0.0158
Kurtosis	-1.0369
CV	50.8094

GRAPH A-1: CEM Distributional Analysis



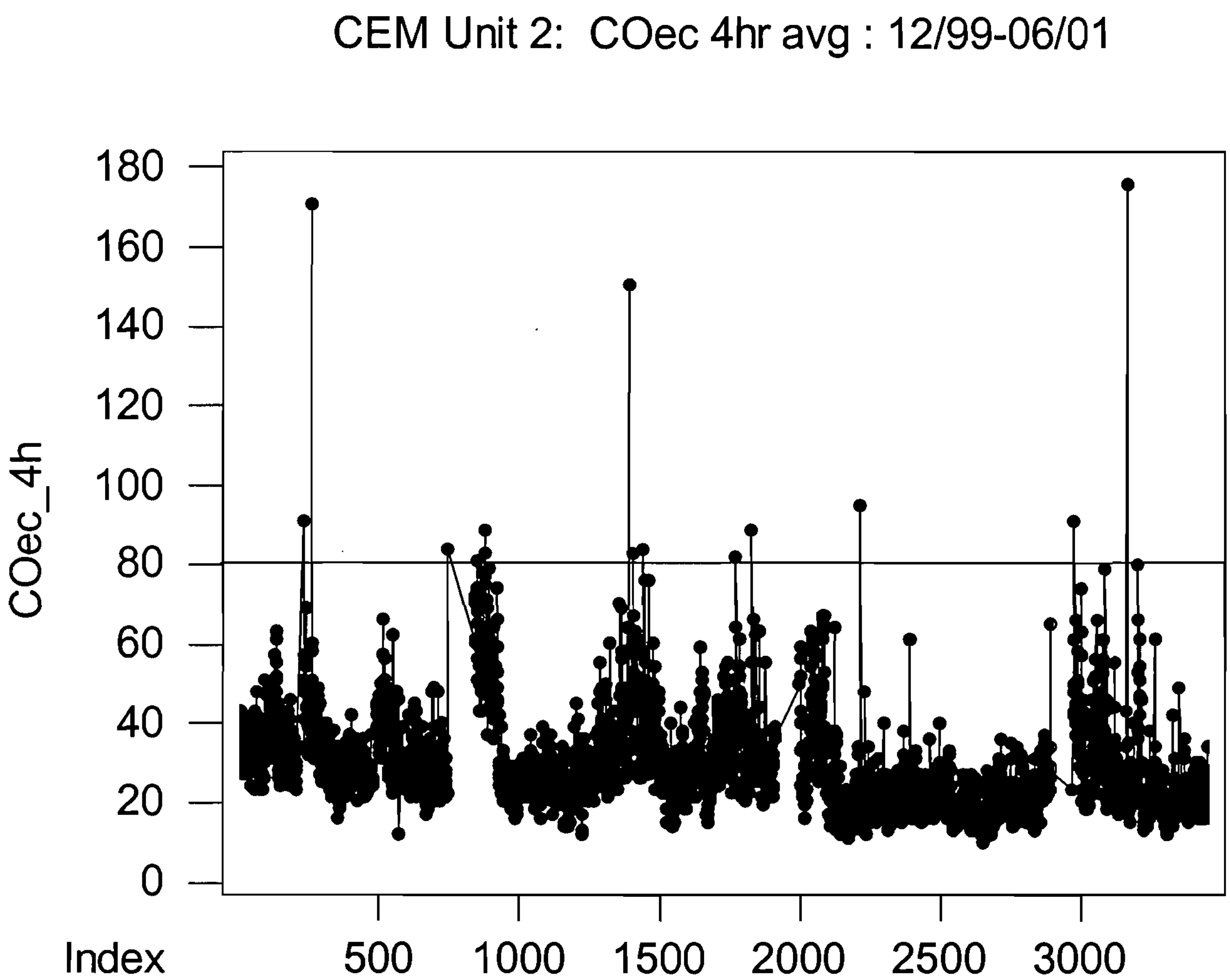
Quantiles

maximum	100.0%	176.00
	99.5%	80.78
	97.5%	61.00
	90.0%	45.00
quartile	75.0%	34.00
median	50.0%	27.00
quartile	25.0%	21.00
	10.0%	17.00
	2.5%	14.08
	0.5%	13.00
minimum	0.0%	10.00

Moments

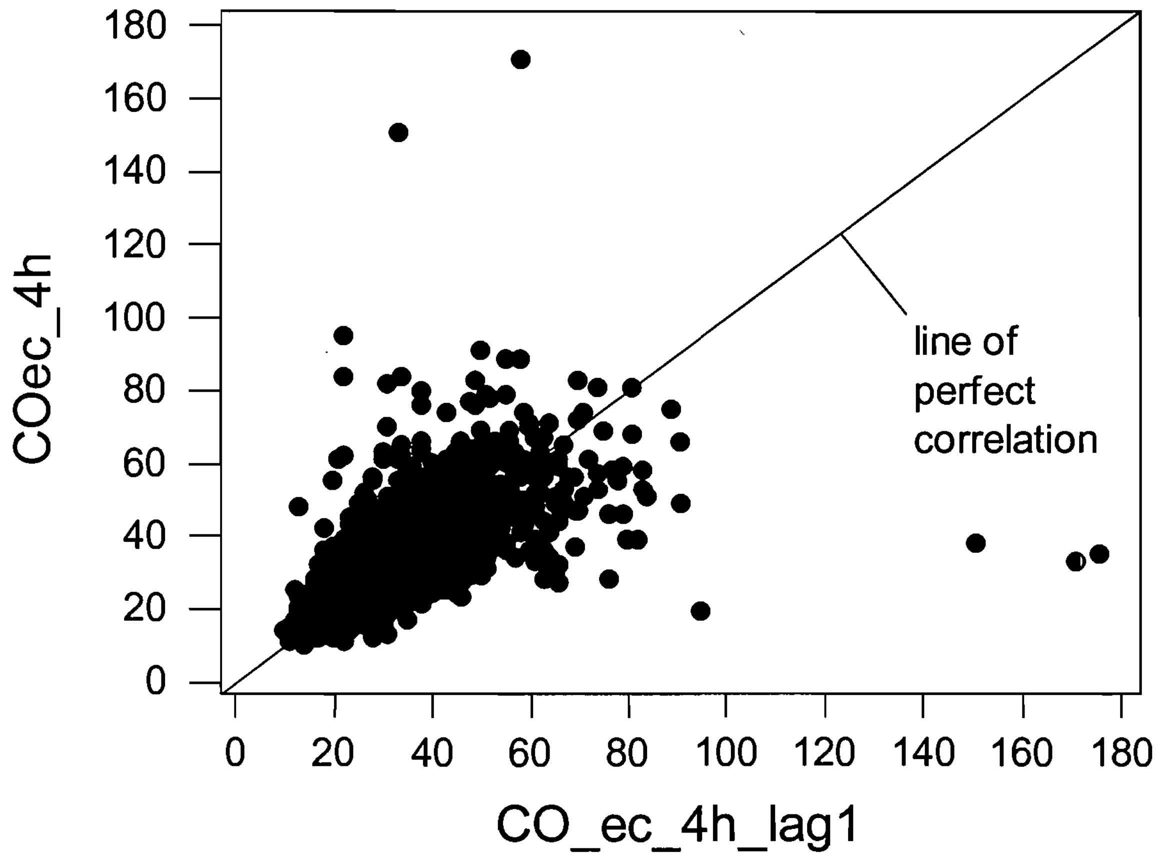
Mean	29.361
Std Dev	12.530
Std Error Mean	0.227
Upper 95% Mean	29.806
Lower 95% Mean	28.915
N	3042.000
Sum Weights	3042.000
Sum	89315.000
Variance	157.012
Skewness	2.523
Kurtosis	16.216
CV	42.678

GRAPH A-2: COec_4h CEM Distributional Analysis



Times series plot of Unit 2 COec data 4-hr averages 12/99-06/01 (chronologically). The large sample 99.5% Upper Prediction Limit is plotted. Notice how the series is relatively stationary and consistent.

GRAPH A-3: COec_4h Chronological Time Series Plot

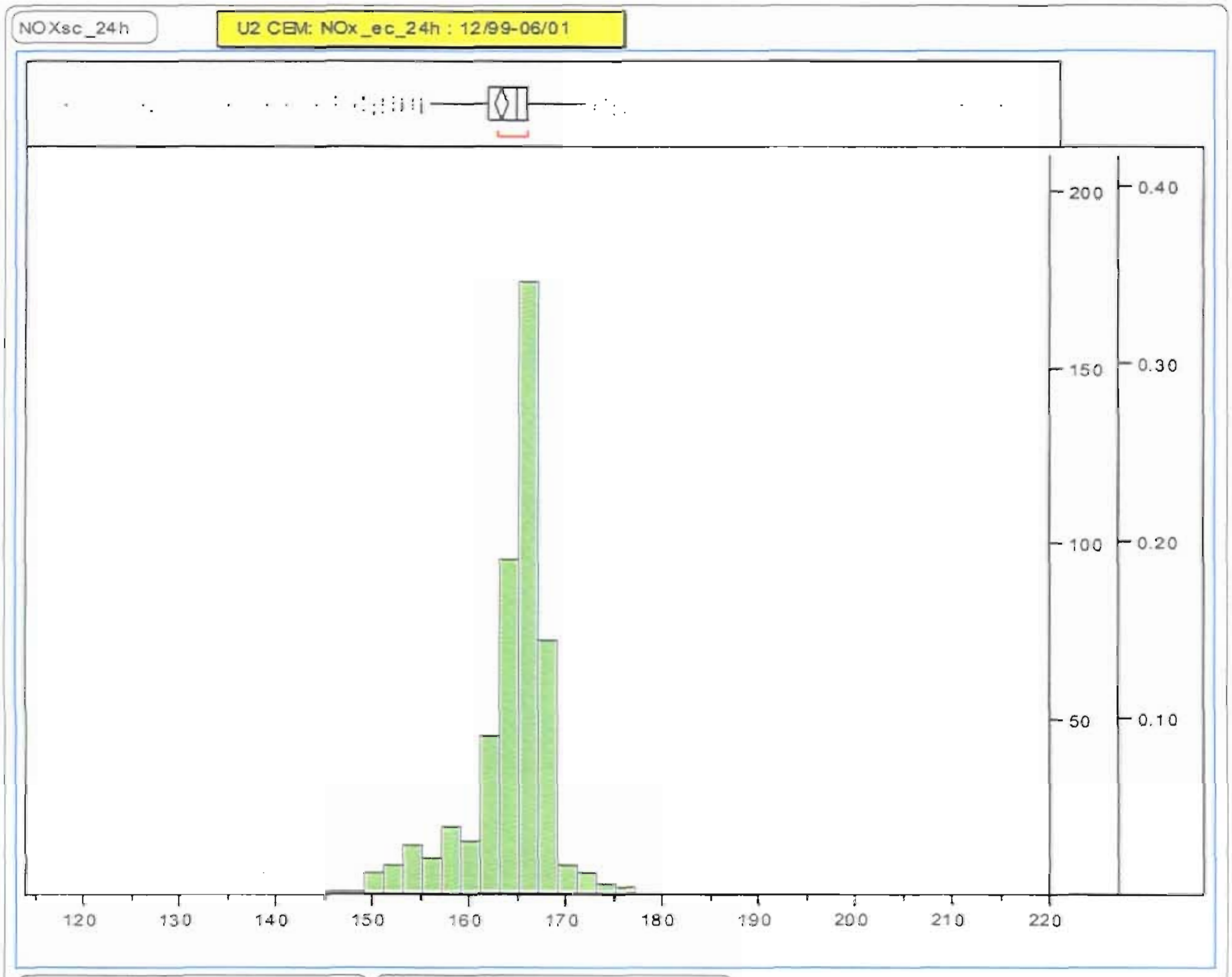


GRAPH A-4: Graphical Representation of CO Autocorrelation

Regression Analysis

```
The regression equation is
COec_4h = 9.06 + 0.691 CO_ec_4h_lag1

3014 cases used 449 cases contain missing values

Predictor          Coef        StDev          T        P
Constant         9.0628       0.4028      22.50    0.000
CO_ec_4h_lag1   0.69080      0.01267      54.54    0.000

S = 8.647       R-Sq = 49.7%      R-Sq(adj) = 49.7%

Analysis of Variance

Source            DF          SS          MS         F         P
Regression         1      222429      222429   2974.67     0.000
Residual Error  3012      225220          75
Total           3013      447649
```

TABLE A-5: Regression Representation of CO Lag 1 Autocorrelation



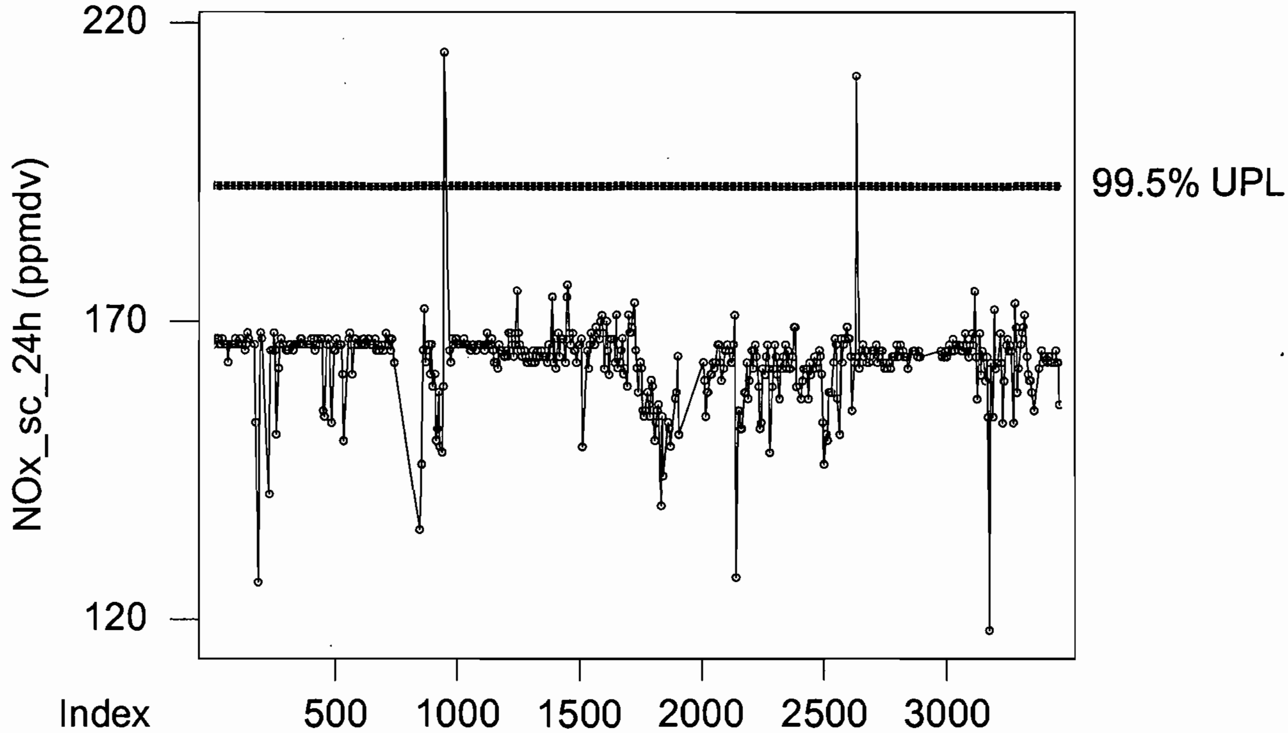
Quantiles

maximum	100.0%	215.00
	99.5%	192.63
	97.5%	171.00
	90.0%	167.00
quartile	75.0%	166.00
median	50.0%	165.00
quartile	25.0%	162.00
	10.0%	155.50
	2.5%	149.00
	0.5%	126.52
minimum	0.0%	118.00

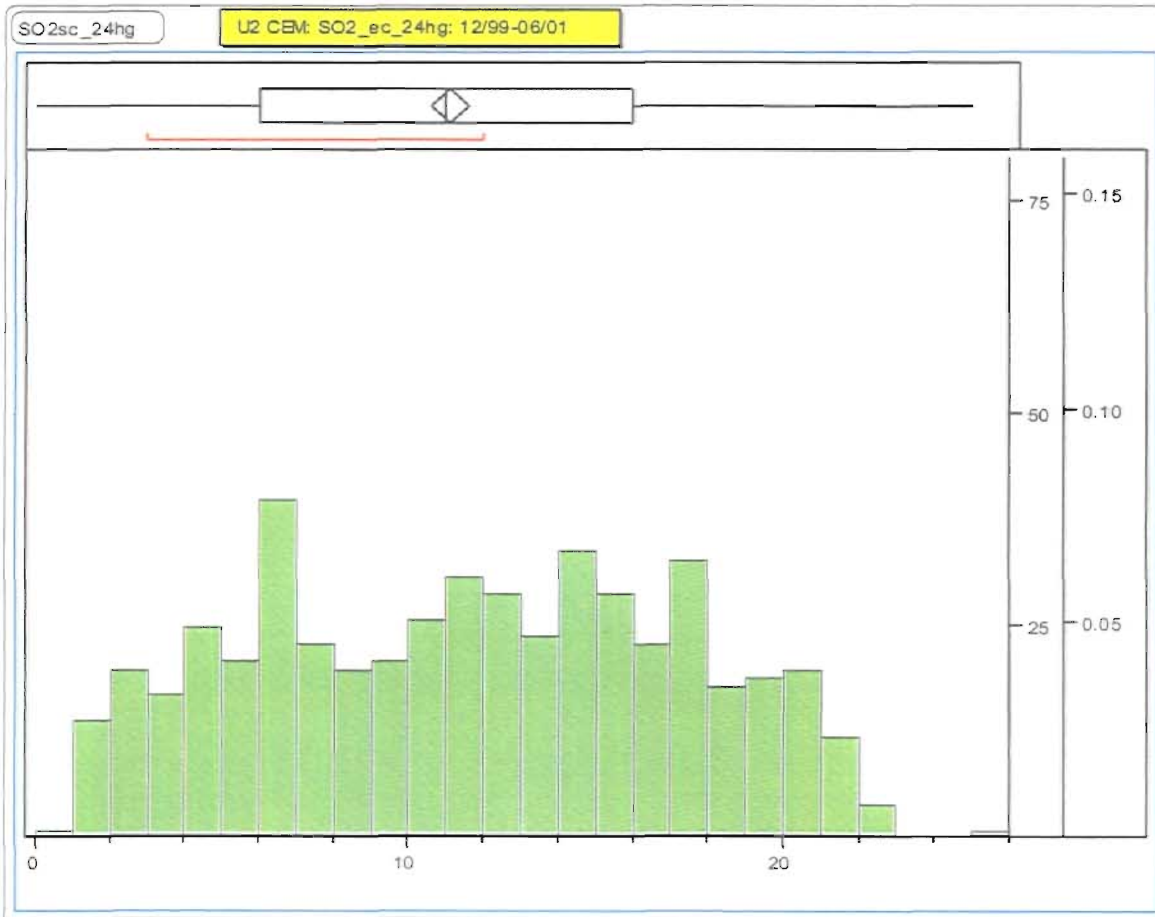
Moments

Mean	163.3750
Std Dev	6.6989
Std Error Mean	0.2984
Upper 95% Mean	163.9613
Lower 95% Mean	162.7887
N	504.0000
Sum Weights	504.0000
Sum	82341
Variance	44.8750
Skewness	-0.3930
Kurtosis	19.6607
CV	4.1003

GRAPH A-6: NO_xsc_24h CEM Distributional Analysis



GRAPH A-7: NO_xsc_24h Chronological Time Series Plot



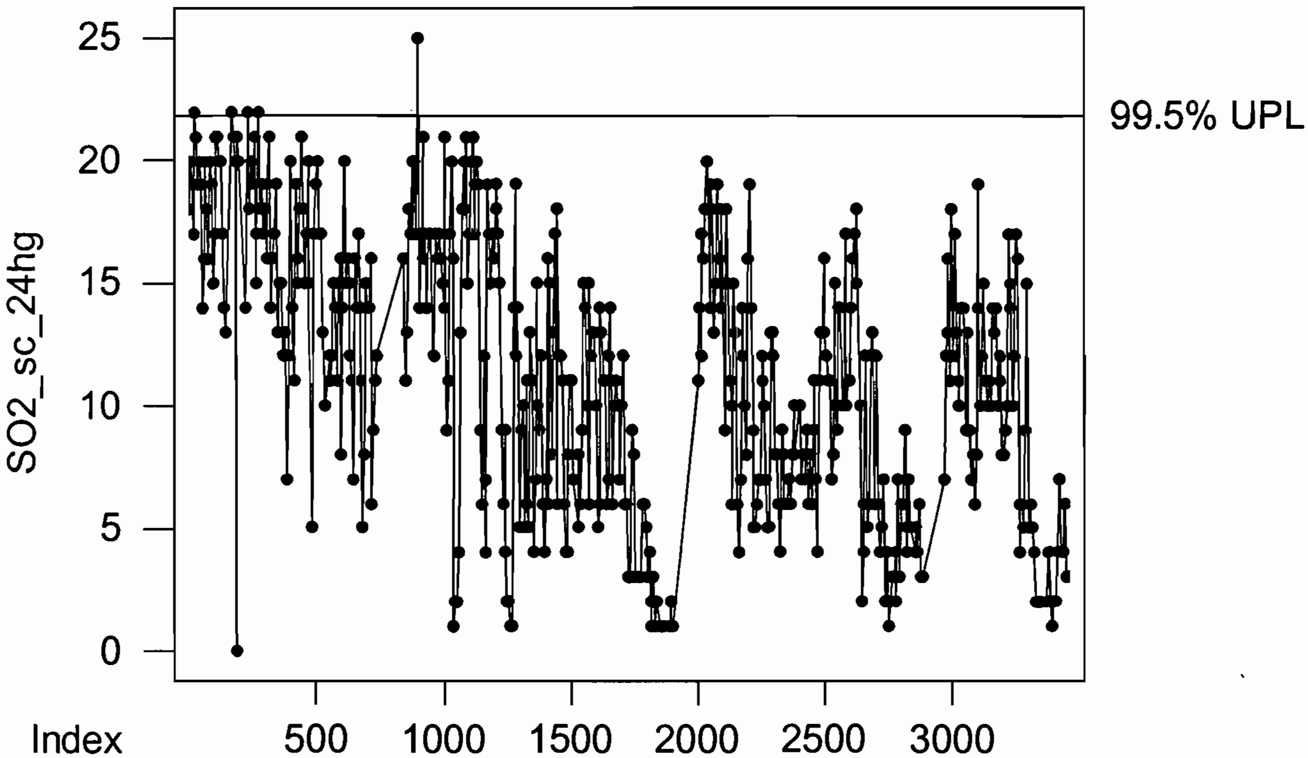
Quantiles

maximum	100.0%	25.000
	99.5%	22.000
	97.5%	21.000
	90.0%	19.000
quartile	75.0%	16.000
median	50.0%	11.000
quartile	25.0%	6.000
	10.0%	3.000
	2.5%	1.000
	0.5%	1.000
minimum	0.0%	0.000

Moments

Mean	11.1109
Std Dev	5.6551
Std Error Mean	0.2516
Upper 95% Mean	11.6053
Lower 95% Mean	10.6165
N	505.0000
Sum Weights	505.0000
Sum	5611.0000
Variance	31.9797
Skewness	-0.0082
Kurtosis	-1.0316
CV	50.8966

GRAPH A-8: SO_2sc_24h CEM Distributional Analysis

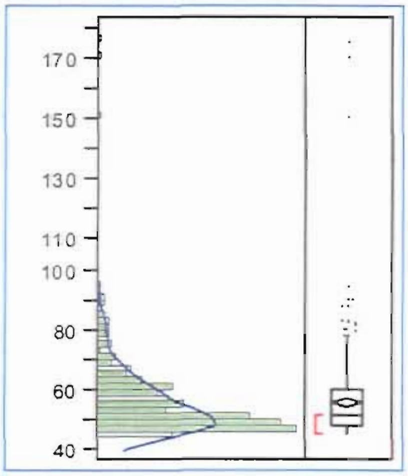


GRAPH A-9: SO_2sc_24h Chronological Time Series Plot

Appendix B:

CEM Upper Tail Exponential Modeling

COec_4h



Kernel Std	
4.147897	

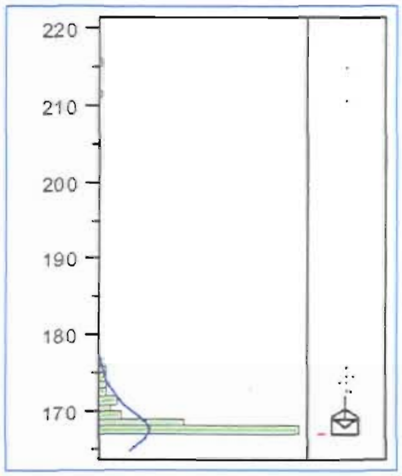
Quantiles

maximum	100.0%	176.00
	99.5%	172.95
	97.5%	88.75
	90.0%	69.80
quartile	75.0%	60.00
median	50.0%	52.00
quartile	25.0%	48.00
	10.0%	46.00
	2.5%	45.00
	0.5%	45.00
minimum	0.0%	45.00

Moments

Mean	56.1246
Std Dev	14.6179
Std Error Mean	0.8159
Upper 95% Mean	57.7298
Lower 95% Mean	54.5194
N	321.0000
Sum Weights	321.0000
Sum	18016
Variance	213.6844
Skewness	4.5058
Kurtosis	30.1840
CV	26.04455

NOxsc_24h



Kernel Std	
2.407976	

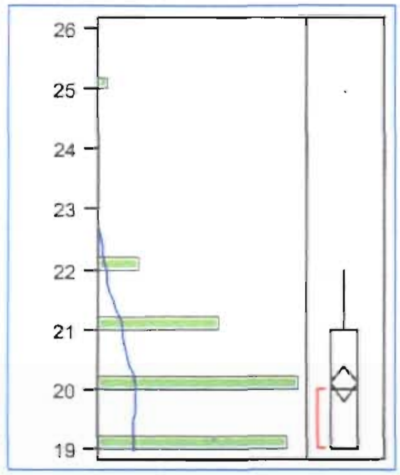
Quantiles

maximum	100.0%	215.00
	99.5%	215.00
	97.5%	194.37
	90.0%	172.10
quartile	75.0%	169.00
median	50.0%	167.00
quartile	25.0%	167.00
	10.0%	167.00
	2.5%	167.00
	0.5%	167.00
minimum	0.0%	167.00

Moments

Mean	169.2041
Std Dev	6.6935
Std Error Mean	0.6761
Upper 95% Mean	170.5461
Lower 95% Mean	167.8621
N	98.0000
Sum Weights	98.0000
Sum	16582
Variance	44.8033
Skewness	5.9511
Kurtosis	37.6492
CV	3.9559

SO2sc_24hg



Kernel Std	
0.458292	

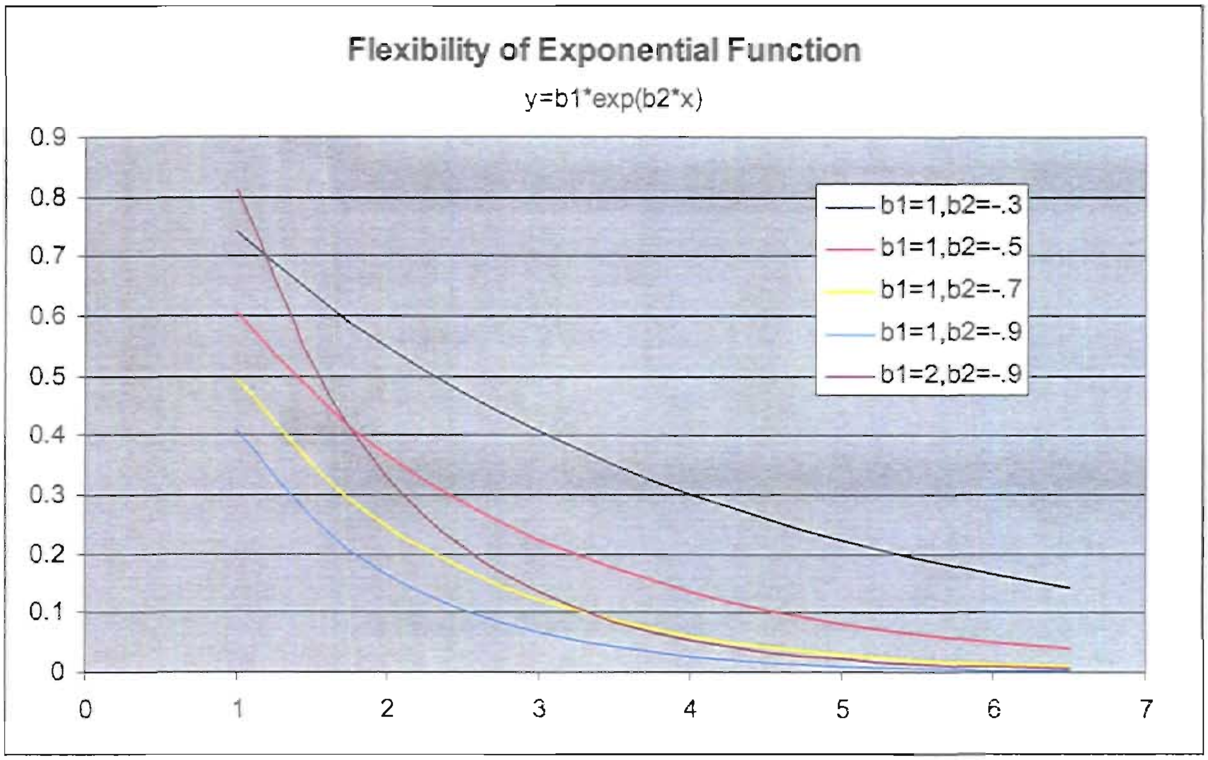
Quantiles

maximum	100.0%	25.000
	99.5%	25.000
	97.5%	23.725
	90.0%	21.300
quartile	75.0%	21.000
median	50.0%	20.000
quartile	25.0%	19.000
	10.0%	19.000
	2.5%	19.000
	0.5%	19.000
minimum	0.0%	19.000

Moments

Mean	20.10714
Std Dev	1.13904
Std Error Mean	0.15221
Upper 95% Mean	20.41218
Lower 95% Mean	19.80211
N	56.00000
Sum Weights	56.00000
Sum	1126
Variance	1.29740
Skewness	1.62034
Kurtosis	4.78805
CV	5.66483

GRAPH B-1: CEM Upper Tails



GRAPH B-2: Representations of Various Exponential Function Forms (b1,b2 = β_1, β_2 of Section Two).

This graph helps explain how CEM Upper Prediction Limits (UPL's) will be calculated. First nonparametric methods will be used to determine the top 10th percentile of values. This upper tail is a smooth, monotonic (constantly decreasing), asymptotic (approaches zero at infinity) function. This class of functions can be readily modeled using the exponential function; Graph B-2 shows how the shape of the exponential function varies with changes in the values of its two parameters (b1 and b2). The x-axis is the value of the constituent variable (ppmdv, etc.); the y-axis is the probability of sampling a value that large from the parent distribution given the specific model parameterization. We will calculate the b1 and b2 coefficients that maximize the fit of the exponential function to the observed upper tail area; then we make predictions based upon the exponential equation about what value of the constituent variable corresponds to the 1hr/yr UPL.

SUMMARY OUTPUT - CO Upper Tail Modeling

Regression Statistics	
Multiple R	0.923976332
R Square	0.853732262
Adjusted R Square	0.853273743
Standard Error	0.370450076
Observations	321

ANOVA

	df	SS	MS	F	Significance F
Regression	1	255.5190049	255.519	1861.932068	3.3497E-135
Residual	319	43.77740949	0.137233		
Total	320	299.2964144			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.140132391	0.082154451	1.705719	0.089033837	-0.021500579	0.301765
X Variable 1	-0.061129407	0.001416669	-43.15011	3.3497E-135	-0.0639166	-0.058342

TABLE B-3: CO Upper Tail Modeling Regression Output

The following regression outputs describe the estimation of the b1 and b2 parameters to be used in the exponential model of the upper tail area.

SUMMARY OUTPUT - NOx Upper Tail Modeling

Regression Statistics	
Multiple R	0.72929306
R Square	0.53186837
Adjusted R Square	0.5230357
Standard Error	0.55251484
Observations	55

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	18.38230351	18.3823	60.21602	2.70958E-10
Residual	53	16.17945018	0.305273		
Total	54	34.56175369			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	12.5296717	2.099743589	5.967239	2.04E-07	8.318121359	16.74122
slope	-0.0957548	0.012339697	-7.759898	2.71E-10	-0.120505074	-0.071005

TABLE B-4: NO_x Upper Tail Modeling Regression Output

SUMMARY OUTPUT - SO2 Upper Tail Modeling

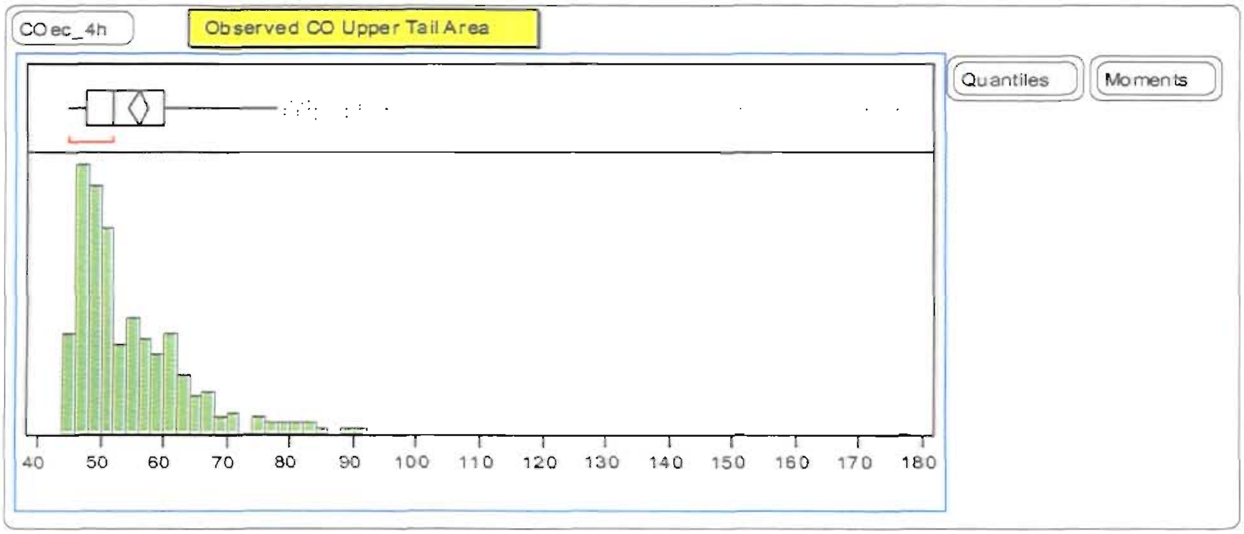
Regression Statistics	
Multiple R	0.939627555
R Square	0.882899942
Adjusted R Square	0.880690507
Standard Error	0.276336661
Observations	55

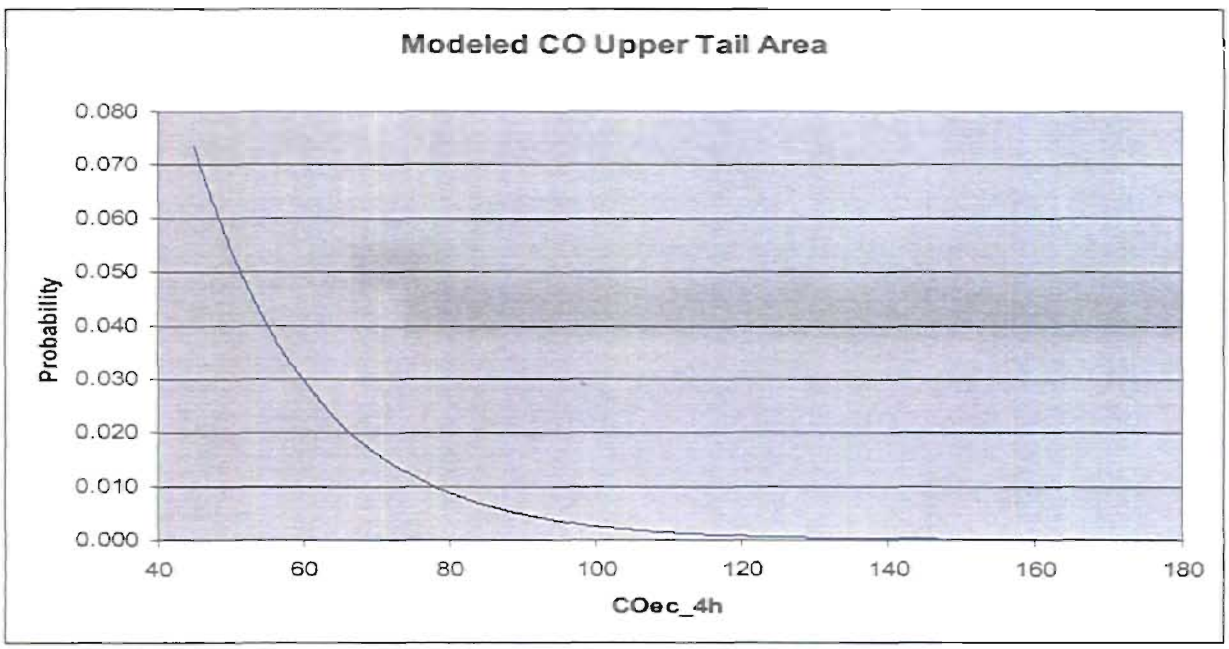
ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	30.51457033	30.51457033	399.6043872	2.40171E-26
Residual	53	4.047183362	0.07636195		
Total	54	34.56175369			

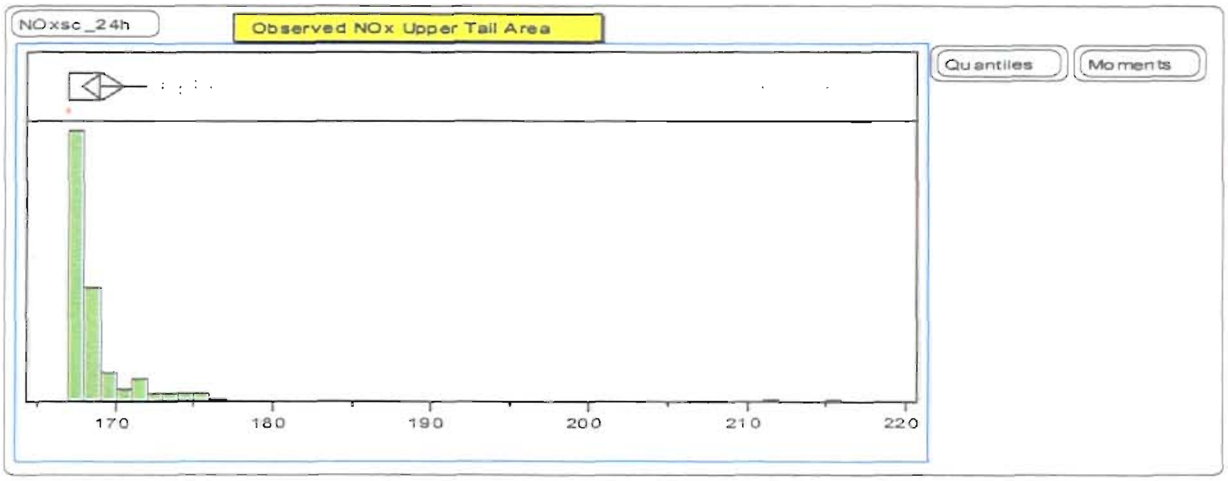
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	12.93868414	0.807905597	16.01509408	5.86613E-22	11.31823149	14.559137
Slope	-0.805914036	0.040315643	-19.9901072	2.40171E-26	-0.886776938	-0.7250511

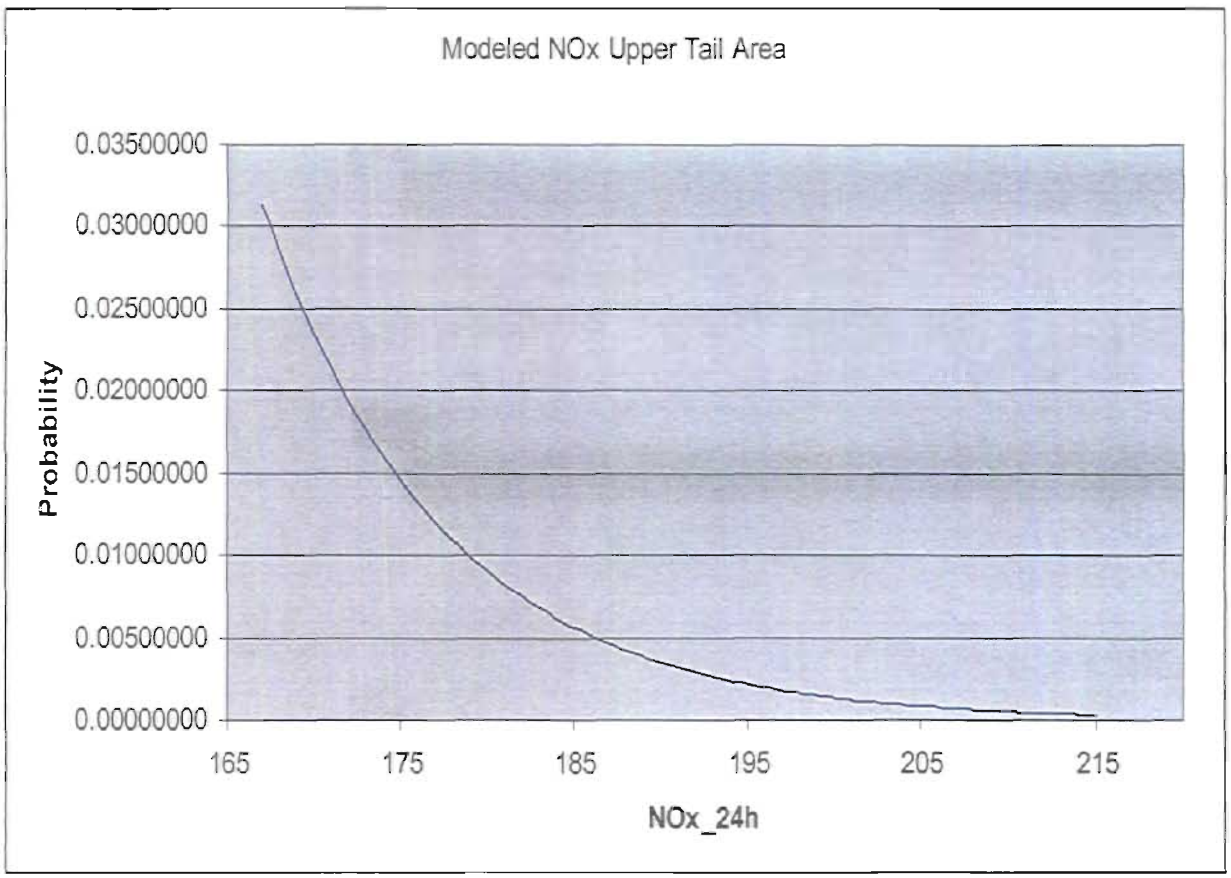
TABLE B-5: SO_2 Upper Tail Modeling Regression Output



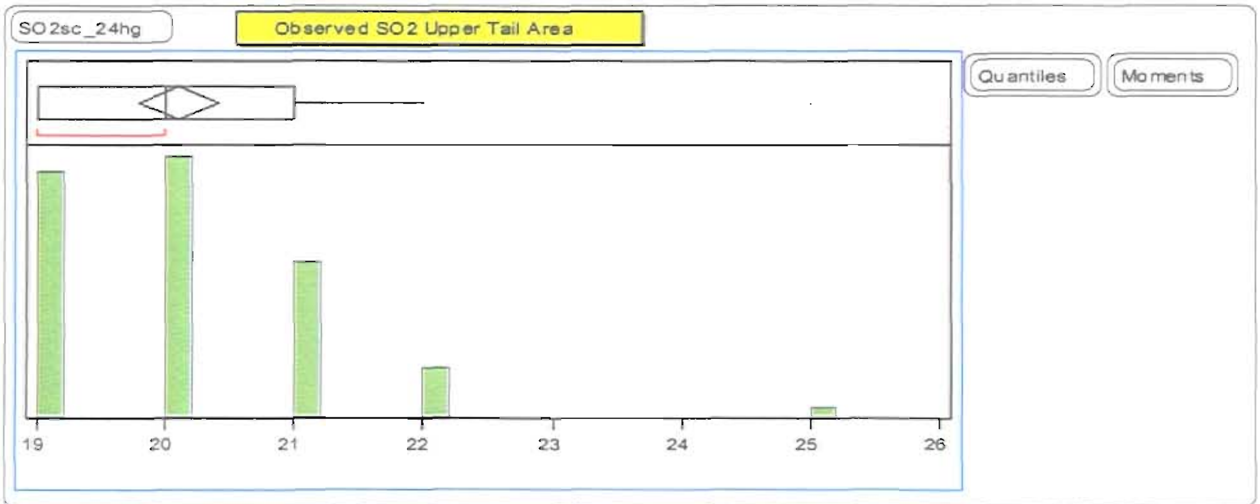


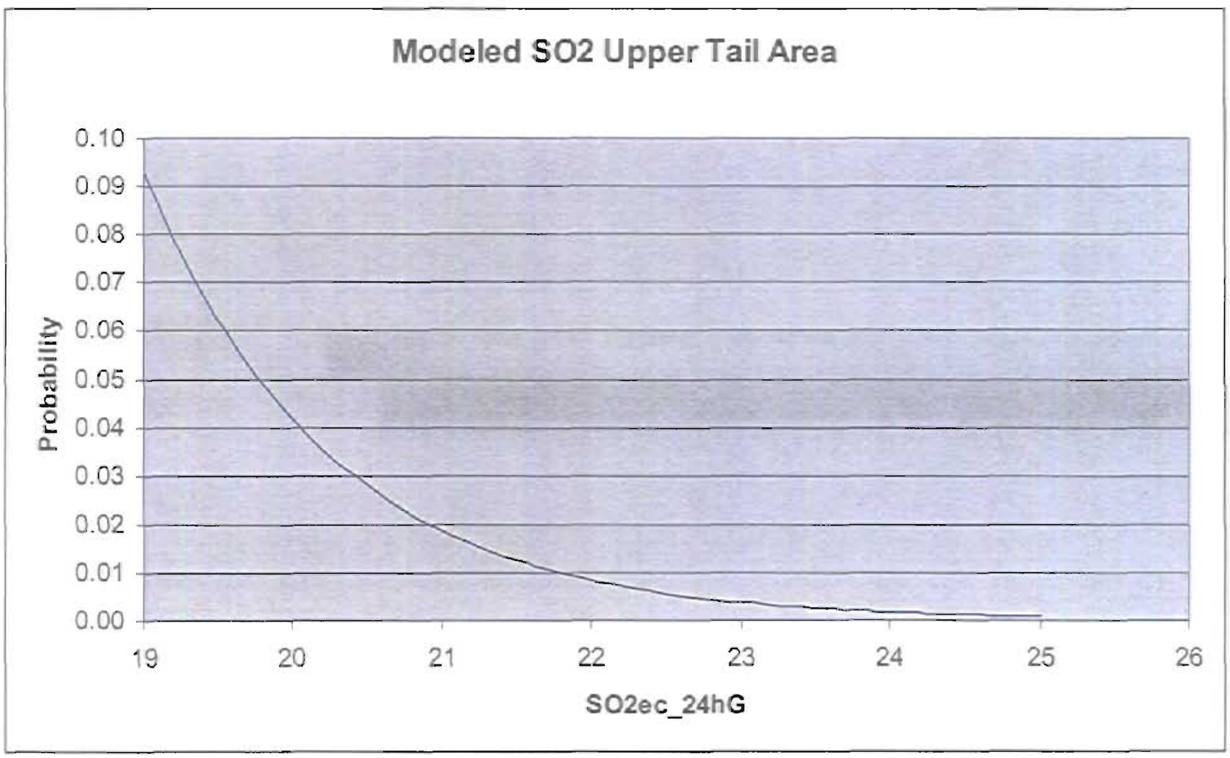
GRAPHS B-6 & B-7: Observed CO Upper Tail Area and Modeled CO Upper Tail Area
Note that the modeled distributions have been normalized such that area under the curve is equal to 0.1000, in accordance with these upper tail areas representing the tenth percentile of the parent distribution.





GRAPHS B-8 & B-9: Observed NOx Upper Tail Area and Modeled NOx Upper Tail Area





GRAPHS B-10 & B-11: Observed SO2 Upper Tail Area and Modeled SO2 Upper Tail Area

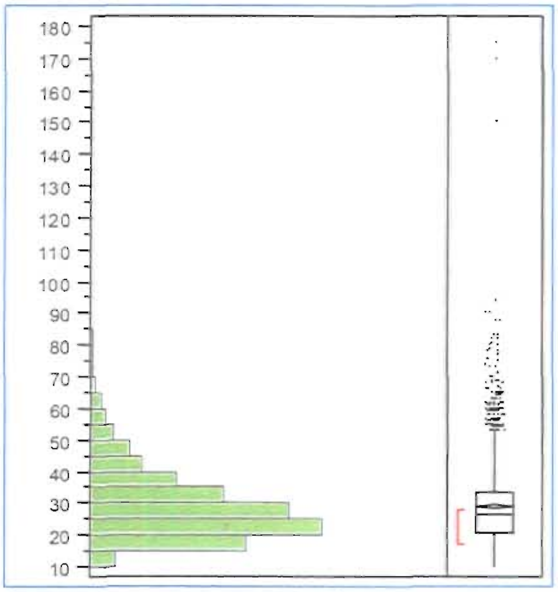
Appendix C:

Stack Constituents, Acceleration factors, and UPL's

GRAPH C-1: Observed Distributions of CO – CEM vs. Stack

TABLE C-4: Stack Constituents and Six Sigma UPL Calculation

COec_4h



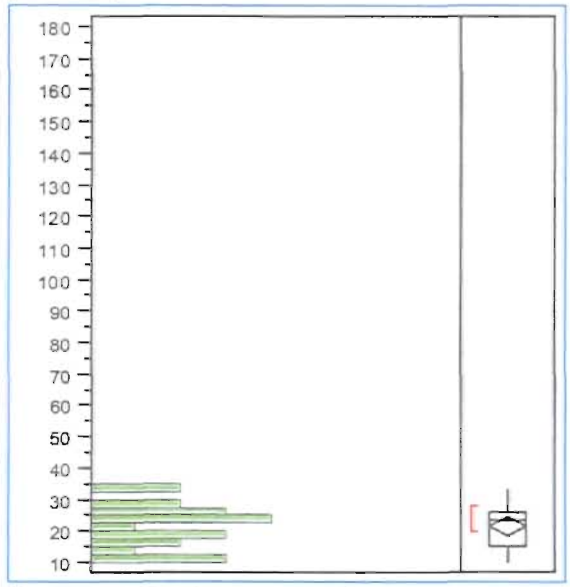
Quantiles

maximum	100.0%	176.00
	99.5%	80.78
	97.5%	61.00
	90.0%	45.00
quartile	75.0%	34.00
median	50.0%	27.00
quartile	25.0%	21.00
	10.0%	17.00
	2.5%	14.08
	0.5%	13.00
minimum	0.0%	10.00

Moments

Mean	29.361
Std Dev	12.530
Std Error Mean	0.227
Upper 95% Mean	29.806
Lower 95% Mean	28.915
N	3042.000
Sum Weights	3042.000
Sum	89315.000
Variance	157.012
Skewness	2.523
Kurtosis	16.216
CV	42.678

CO_stack



Quantiles

maximum	100.0%	33.100
	99.5%	33.100
	97.5%	33.100
	90.0%	32.120
quartile	75.0%	26.300
median	50.0%	24.000
quartile	25.0%	15.250
	10.0%	11.660
	2.5%	10.600
	0.5%	10.600
minimum	0.0%	10.600

Moments

Mean	21.60476
Std Dev	6.81986
Std Error Mean	1.48822
Upper 95% Mean	24.70910
Lower 95% Mean	18.50042
N	21.00000
Sum Weights	21.00000
Sum	453.70000
Variance	46.51048
Skewness	-0.07860
Kurtosis	-0.97873
CV	31.56646

GRAPH C-1: Observed Distributions of CO – CEM vs. Stack

Six Sigma: 3.4 ppm = 3.400E-06

Constituent	units	n	Avg Stack Test	SD Stack Test	Accel.Factor	SD_adj	t-value	Six Sigma UPL
			D	E	F	G=(ExF)	0.0000034	(D + (GxH))
VOC/NMHC (1)	ppmdv@7%O2	18	1.764	1.539	2.688	4.138	6.929	30.43
HF (1)	ppmdv@7%O2	18	0.09702	0.05133	2.688	0.1380	6.929	1.053
Be(1)	mcg/dscm@7%O2	15	0.00005713	0.00003506	2.688	0.00009423	7.749	0.0007873
Cd	mcg/dscm@7%O2	12	0.0009106	0.0004663	2.688	0.001254	9.239	0.01249
PM	gr/dscf@7%O2	21	0.001464	0.0009501	2.688	0.002554	6.482	0.01802
Hg	mcg/dscm@7%O2	21	31.70	14.79	2.688	39.76	6.482	289.4
HCl	ppmdv@7%O2	21	21.90	9.679	2.688	26.02	6.482	190.5
Total PCDD/F	ng/dscm@7%O2	21	9.871	9.631	2.688	25.89	6.482	177.7
Pb	mcg/dscm@7%O2	21	0.006277	0.006152	2.688	0.01654	6.482	0.1135

(1) VOC, HF, Be: No NSPS standard, PSD limit from existing Units 1& 2
Permit limit for NH3 not addressed as no operational history for 150 ppmdv NOx limit
Note: The emission limits presented above do not include the removal efficiency standard provided by 40 CFR Part 60, subpart Eb or the time-weighted averages for pollutants requiring continuous monitoring. The removal efficiency is 85% for Hg, 80% for SO2, and 95% for HCl.

TABLE C-4: Stack Constituents and Six Sigma UPL Calculation

Appendix D:

What is an Upper Prediction Limit?

An Upper Prediction Limit (UPL) is an estimated numerical value such that we would only expect to see samples with values exceeding the UPL a specified percentage of time. For example, a Six Sigma UPL corresponds to 3.4 readings per million that exceed the UPL bound, approximately 125 years of operation. It is based on statistical reliability theory, and represents the quantitative value such that the probability of compliance during any one-hour sampling period exceeds 99.999%.

UPL's can be calculated from several methods. **Nonparametric** methods assume nothing; they look at the observed data and through rank ordering processes make descriptive declarations about the sample – "hey, here's the upper 10th percentile of the sample". **Empirical** models are applied for mathematical convenience – "say, that curve looks like an exponential decay curve, can we adequately model it"? **Distributional** modeling provides the most information (it's Normal, or Weibull, or...), but with the most amount of restrictions (that when violated, result in errors with varying manifestations in the system). Each of the modeling methods has its appropriate place in a scientific analysis, and when applied synergistically, will characteristically deliver superior predictive performance.

STACK				
Constituent	units	Six Sigma UPL	NSPS limit	Appl_Lim
VOC/NMHC (1)	ppmdv@7%O_2	30.43	37.00	Six Sigma UPL
HF (1)	ppmdv@7%O_2	1.053	5.000	Six Sigma UPL
Be(1)	mcg/dscm@7%O_2	0.0007873	0.0001590	NSPS limit
Cd	mg/dscm@7%O_2	0.01249	0.02000	Six Sigma UPL
Pb	mcg/dscm@7%O_2	0.1135	0.2000	Six Sigma UPL
PM	gr/dscf@7%O_2	0.01802	0.01000	NSPS limit
Hg	mcg/dscm@7%O_2	289.4	70.00	NSPS limit
HCl	ppmdv@7%O_2	190.5	25.00	NSPS limit
Total PCDD/F	ng/dscm@7%O_2	177.7	13.00	NSPS limit
CEM				
Constituent	units	Six Sigma UPL	NSPS limit	Appl_Lim
NOx	ppmdv@7%O2	262.4	150.0	NSPS limit
SO2	ppmdv@7%O2	31.68	29.00	NSPS limit
CO	ppmdv@7%O2	150.8	100.0	NSPS limit

(1) VOC, HF, Be: No NSPS standard, PSD limit from existing Units 1& 2
Permit limit for NH3 not addressed as no operational history for 150 ppmdv NOx limit
Note: The emission limits presented above do not include the removal efficiency standard provided by 40 CFR Part 60, subpart Eb or the time-weighted averages for pollutants requiring continuous monitoring. The removal efficiency is 85% for Hg, 80% for SO2, and 95% for HCl.

TABLE D-1: Six Sigma UPL v. NSPS Limits.