FINAL TECHNICAL REPORT

“Mercury Specie and Multi-Pollutant Control”

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Disclaimer

Abstract

This report is the Final Technical Progress Report submitted by NeuCo, Inc., under Award Identification Number, DE-FC26-06NT42389. This award is part of the Clean Coal Power Initiative ("CCPI"), a cost-shared partnership between the Government and industry to develop and demonstrate advanced coal-based power generation technologies at the commercial scale.

This report is one of the required reports listed in Attachment B, the Federal Assistance Reporting Checklist, which is part of the Cooperative Agreement. The report covers the whole award period (April 12, 2006 – May 31, 2010) and NeuCo's efforts to design, develop, and deploy on-line optimization systems during that period.

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1 Introduction

This project was awarded to demonstrate the ability to affect and optimize mercury speciation and multi-pollutant control using non-intrusive advanced sensor and optimization technologies. The intent was to demonstrate plant-wide optimization systems on a large coal fired steam electric power plant in order to minimize emissions, including mercury (Hg), while maximizing efficiency and maintaining saleable byproducts. Advanced solutions utilizing state-of-the-art sensors and neural network-based optimization and control technologies were proposed to maximize the removal of mercury vapor from the boiler flue gas thereby resulting in lower uncontrolled releases of mercury into the atmosphere.

- Budget Period 1 (Phase I)
  - Included the installation of sensors, software system design and establishment of the as-found baseline operating metrics for pre-project and post-project data comparison.
- Budget Period 2 (Phase II)
  - Software was installed, data communications links from the sensors were verified, and modifications required to integrate the software system to the DCS were performed.
- Budget Period 3 (Phase III)
  - Included the validation and demonstration of all control systems and software, and the comparison of the optimized test results with the targets established for the project site.

This report represents the final technical report for the project, covering the entire award period and representing the final results compared to project goals.

NeuCo shouldered 61% of the total project cost; while DOE shouldered the remaining 39%. The DOE requires repayment of its investment. This repayment will result from commercial sales of the products developed under the project. NRG’s Limestone power plant (formerly owned by Texas Genco) contributed the host site, human resources, and engineering support to ensure the project’s success.

2 Executive Summary

2.1 Background

The Mercury Specie and Multi-Pollutant Control project described in this report set out with two major goals. The first goal was to deploy a suite of advanced instrumentation and optimization systems. The second goal was to use these systems in an integrated way to improve unit operations across a variety of performance objectives, including mercury (Hg) removal.

The following report describes the systems that were deployed and evaluated at Unit 2 of the Limestone power plant (LMS U2), the optimization scheme used to integrate the deployed systems and the results seen with respect to optimization objectives.

These objectives included the following target improvements:

- Optimization of plant's overall performance through an optimization system that will arbitrate among the point solutions of individual pieces of equipment.
- NOx – Target of 10% reduction in NOx emissions.
- Heat Rate – Target improvement of 0.5-2.0% as shown using PerfIndex and/or ASME part 4 calculations.
- Hg (mercury) – Target of 40% post combustion mercury capture though optimized mercury speciation.
- Increased Operating Controllability and Flexibility.
- Reduced Fuel Consumption 0.5-2.0% normalized to fuel type and kWh generation.
- Reduced Capital Investment Compared to Alternative Emissions Reduction Systems.

To achieve these goals the cooperative agreement specified that the following technologies be evaluated and/or deployed.

Intelligent Fuel Management System (FMS)
The FMS is composed of the Combustion Optimization System, the Ready Engineering Coal Fusion System, and Sabia's elemental analyzer.

Mercury Specie Control System
The Mercury Specie Control System includes the boiler area optimization, sensors from Zolo, PS Analytical, and Triple 5 with Mercury emissions being measured through Continuous Emission Monitors (CEMS) by PS Analytical (PSA).

Advanced Electrostatic Precipitator (ESP) Optimization System
The ESP Optimization System is composed of a Carbon-In-Ash (CIA) virtual online analyzer, a CIA sensor from ABB, and ESP Optimization software.

Advanced Intelligent Soot Blowing (ISB) System
The ISB system is composed of SootOpt® Intelligent Sootblowing software

Advanced Flue Gas Desulfurization (FGD) Optimization System
The FGD system is composed of optimization software developed during the course of this project.

Intelligent Plant Optimization
The Intelligent Plant Optimization system is software that ensures that all of the other optimization systems developed as part of this project are working together effectively.

The technologies specified for the project included a wide variety of hardware instrumentation, in addition to the software-based optimization systems needed to take advantage of them. Figure 1 shows the mapping of instrumentation technologies deployed across the functional areas of LMS U2 as part of the project.

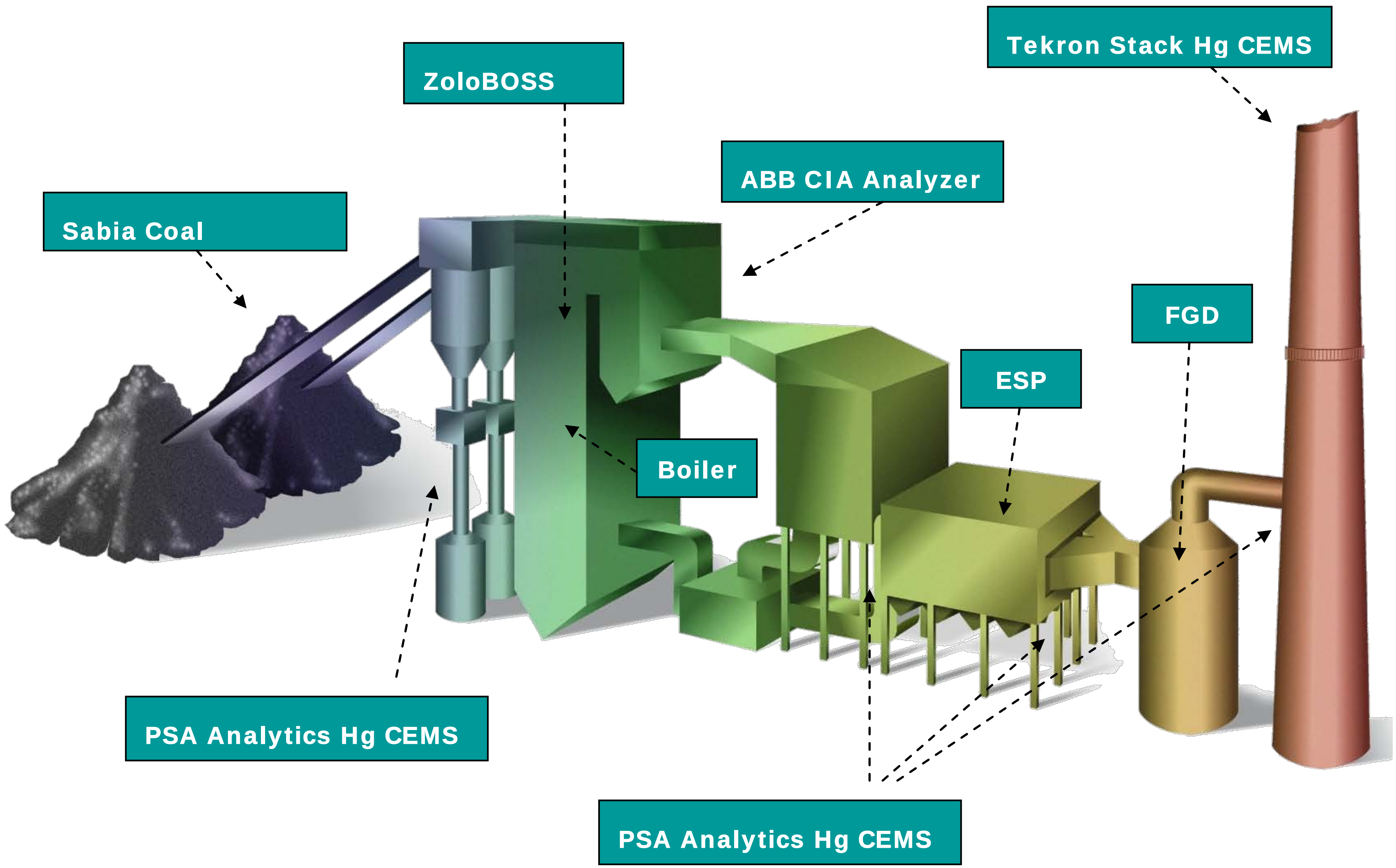

Figure 1: Mapping of Advanced Instrumentation Deployed and Evaluated

2.2 Execution Timeline

The execution of the project was divided into three phases.

- Budget Period 1 (Phase I) involved primarily the installation of advanced instrumentation to be evaluated as part of the project.
- Budget Period 2 (Phase II) involved installation of optimization software, data and closed-loop control integration, and verification of the instrumentation installed in Phase I.
- Budget Period 3 (Phase III) consisted of the validation and demonstration of the optimization systems and software, and the analysis of test results.

2.3 Execution Challenges

Main challenges to project execution, in order of impact, consisted primarily of the following:

- Maintenance of good Hg CEMS data at the ESP inlet, FGD Inlet and FGD outlet;
- Changing regulatory and market conditions;
- Installation and maintenance of wide array of instrumentation from multiple vendors;
- Remote management of network cluster and evolving NERC requirements; and
- Achieving high rates of optimization technology utilization.

These challenges are discussed in detail throughout Section 3.

2.4 Benefits, Key Learnings, and Conclusions

2.4.1 Benefits

Despite the challenges described above, the project delivered significant "hard" benefits against the specified project objectives. Table 1, Table 2, and Table 3 show the comparison on population means analysis used to estimate the effect of combustion and heat transfer optimization on plant performance. The analysis is detailed in Section 3.6.

NOx production was reduced by 16%, at the same time CO was reduced by 24%. Losses Efficiency shows an improvement of 0.5%, with a heat rate improvement of between 0.52% and 1.2%. Operating flexibility is a significant part of the optimization story, in that the host unit was able to significantly change its fuel blend, while also gaining improved control over combustion and heat transfer processes.

With respect to mercury emissions, when fuel blend control, using the Ready Engineering CoalFusion system , is included, total stack mercury emissions are reduced from around 6.95µg/m^3 to around 5.4µg/m^3, a delta of around 22%.

Table 1 shows mercury performance using two models or Virtual On-Line Analyzers. One model predicts total stack mercury emissions. The other predicts mercury removal. The development of these models is detailed in Section 3.5.

The mercury removal percentage shown in Table 1 is modest at 2.3%. This value is lower than expected, one possible reason being that the model used does not include an input for the effect of Fuel Blend since insufficient blend data was available for periods when the mercury analyzers in the ESP and FGD areas, which are required to establish a removal estimate, were working properly.

The total stack mercury reduction is computed as 5% as shown in Table 1. This is non-fuel blending related improvement, as fuel blend was steady during the period shown in the analyzed data (though fuel blend was an input to this model).

3/31/10 - 7/9/10, 15m, MW>880, ON Plus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
Hg Stack Total (VOA)	$\mu g/m^3$	5.48	5.21	-0.27	-4.9%	Down
Hg Removal	%	62.18	63.63	1.45	2.3%	Up

Table 1: Tabulated Comparison of KPIs Hg (non-fuel related optimization)

Other benefits included improvements to the variability of some key performance indicators (KPIs) as shown in Table 2. In all cases such KPIs represent some proxy for a bottom line emissions, efficiency or availability/reliability effect. In addition to the benefits shown with the comparison of populations' analysis, a number of benefits in the form of avoided equipment, availability and reliability issues were seen, though it is difficult to provide hard estimates of the impact of avoided problems over time. In all cases such KPIs represent some proxy for a bottom line emissions, efficiency or availability/reliability effect, though they are often hard to quantify directly. These are also discussed in Section 3.6.

3/31/10 - 7/9/10, 15m, MW>880, ON Plus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
NOx	lb/MMBtu	0.218	0.182	-0.036	-16.5%	Down
CO	ppm	33.08	25.15	-7.93	-24.0%	< 40
RH Temp A	degF	995.78	994.51	-1.27	-0.1%	>980
RH Temp B	degF	995.51	993.91	-1.6	-0.2%	>980
O2 A	%	3.05	2.68	-0.37	-12.1%	>2
O2 B	%	2.94	2.86	-0.08	-2.7%	>2
Boiler O2	%	3	2.77	-0.23	-7.7%	>2
Tilt Dmd A	%	70.87	56.27	-14.6	-20.6%	Down
Tilt Dmd B	%	66.73	59.26	-7.47	-11.2%	Down
2A APH Gas Inlet	degF	779.58	774.37	-5.21	-0.7%	<780
2B APH Gas Inlet	degF	771.25	767.29	-3.96	-0.5%	<780

3/31/10 - 7/9/10, 15m, MW>880, ON Plus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
Losses Effic	%	81.84	81.84	0	0.00%	Up
Net Unit HR	Btu/kWh	10323.46	10202.99	-120.47	-1.17%	Down
Net Turbine HR (Corr)	Btu/kWh	8261.55	8218.69	-42.86	-0.52%	Down

Table 2: Tabulated Comparison of KPIs (non-Hg) (non-fuel related optimization)

3/31/10 - 7/9/10, 15m, MW>880, ON Plus O2 and Tilts					
Disturbance	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**
Load	MW	902.55	905.43	2.88	0.3%
Fuel Heating Value	Btu/lb	6389.93	6387.07	-2.86	-0.04%
PCT PRB	%	52.65	55.64	2.99	5.68%
Cond BP	inH2O	2.19	1.86	-0.33	-15.07%
Ambient	degF (wetbulb)	84.88	76.34	-8.54	-10%

Table 3: Tabulated Comparison of Disturbance Factors

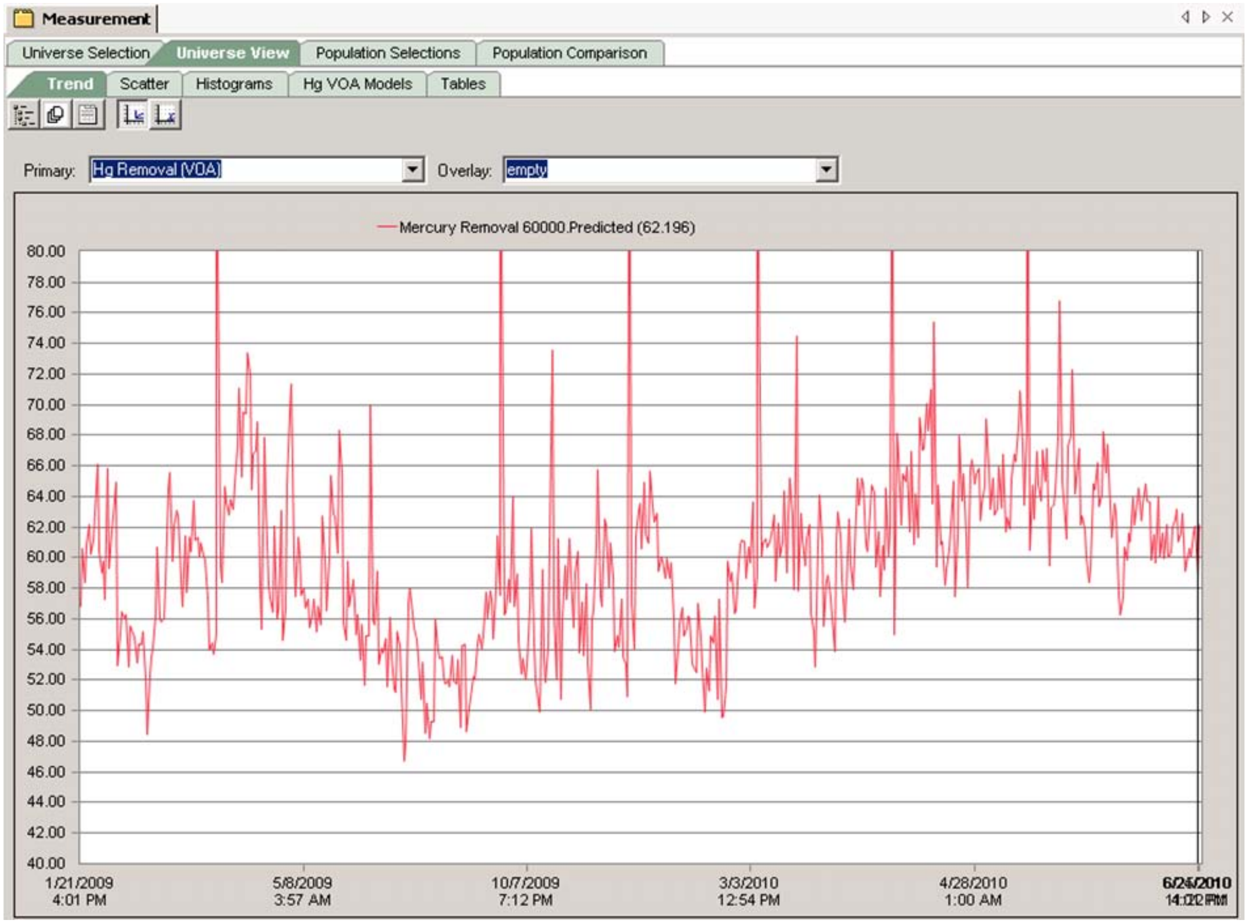

Figure 2: Hg Removal (VOA) and Utilization Index, Unit Load >880 MW, 1/21/09-6/25/10

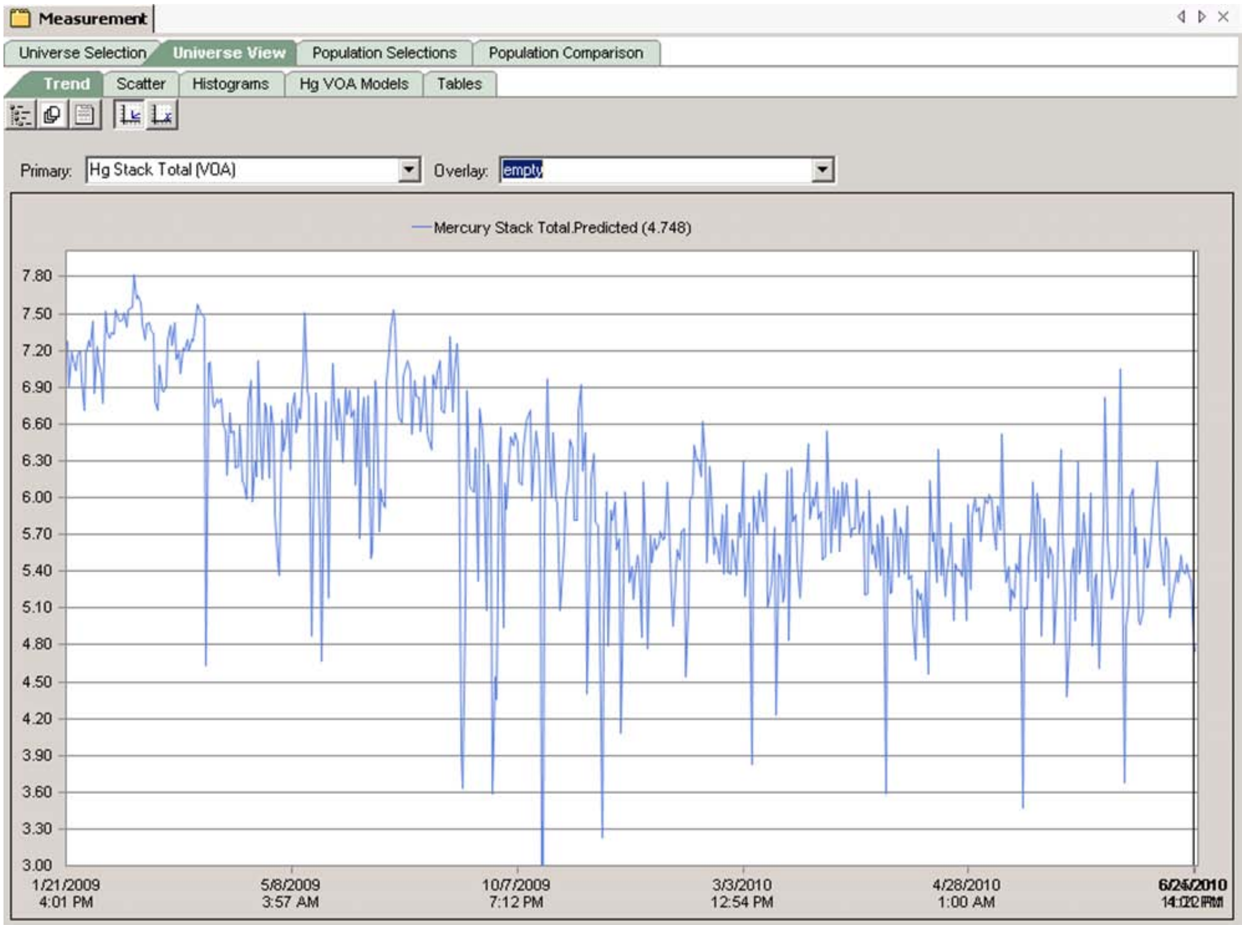

Figure 3: Mercury Stack Total (VOA), Unit Load >880 MW, 1/21/09-6/25/10

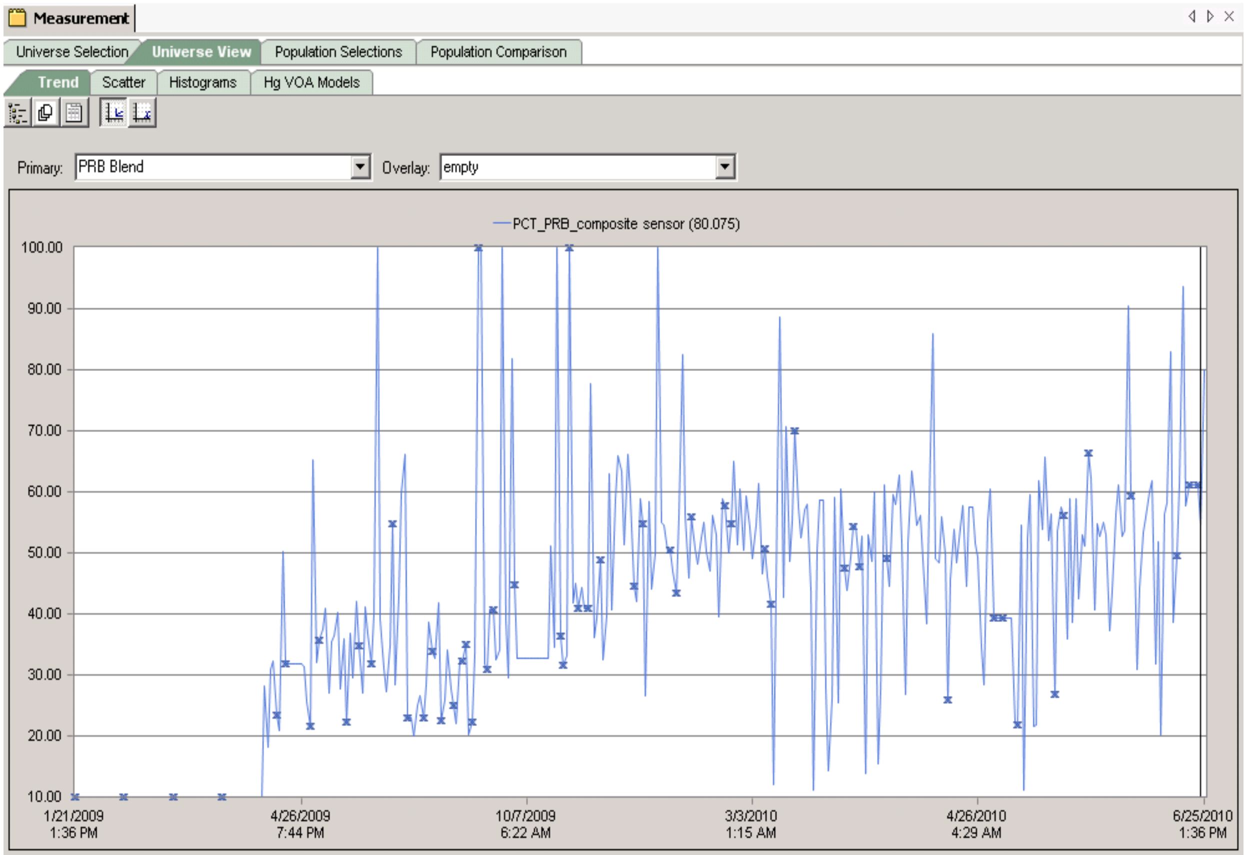

Figure 4: PCT PRB Blend, Unit Load >880 MW, 1/21/09-6/25/10

Table 2 shows only the data from the comparison of populations. In addition, a number of benefits in the form of avoided equipment, availability and reliability issues were seen. It is very difficult to provide hard estimates of the impact of avoided problems over time. Where possible, estimates are given.

2.4.2 Economic Implications

This section summarizes the results of an engineering-economics benefits analysis applied to the Limestone results and also to the entire US fleet of fossil-fired generating units, assuming the technology benefits demonstrated at Limestone are broadly applicable.

2.4.2.1 Fuel Efficiency

Limestone's fuel costs and actual unit heat rate values factor into NRG's operation of the plant within ERCOT and are thus considered proprietary. For the purposes of this report, a heat rate of 10,000 Btu/kWh was used for all three units, along with a $1.50/mmBtu for delivered coal. These values are representative of pulverized coal-fired units burning a blend of Powder River Basin ("PRB") Coal and Lignite coal. Fuel prices for units burning 100% PRB, a blend of PRB and bituminous coal, or all bituminous coal are higher, and will be reflected in the aggregate US generation industry analysis at the end of this section.

The annual dollar value associated with the average 0.86% heat rate improvement described in the prior section with an average fuel cost of $1.50/mmBtu would equate to fuel savings of approximately $928,500 dollars per year.

2.4.2.2 NOx reduction

The current value of NOx reduction at Limestone, as with other generating units in states covered by the EPA, CAIR regulations and the Transport Rule that is replacing it is currently in a state of flux. For the purposes of this document, we have used the average of the range between $500 and $1,000 per ton estimated average compliance costs (i.e. $750) for the Transport Rule scheduled to go into effect January 1, 2012.

The annual dollar value associated with the 16% average NOx reduction described above with an average allowance value of $750 per ton would equate to a benefit of approximately $830,500 dollars per year at Limestone 2.

2.4.2.3 Availability

As noted earlier in the report, optimization benefits with respect to reliability and commercial availability are difficult to precisely quantify, however they clearly provided a substantial benefit as indicated in the following examples:

- Several of the equipment health-related anomalies detected and diagnosed through MaintenanceOpt may -- if not identified in a timely manner by plant personnel -- have resulted in either forced outages themselves or lengthened the duration of outages experienced for other reasons.
- The selective boiler cleaning performed by SootOpt avoids unnecessary cleaning of heat transfer surfaces that are already clean, thus reducing erosion, stress, and thermal cracking. While we cannot directly relate this to a reduction in tube rupture outages, there is strong reason to believe that less cleaning of already clean surfaces can be expected to help reduce such outages, which are the largest contributor to forced outage rates at all coal-fired plants.
- The on-belt fuel blending facilitated by the project not only reduces upsets due to uncontrolled variability in coal quality, but also provides substantially greater flexibility with respect to when a given pulverizer can be repaired or maintained.
- The reduced process variability and heightened process and situational awareness resulting from all four of the optimizers has likely reduced upsets, adverse operating conditions, and the associated wear and tear on unit equipment.

Given the difficulties in precisely quantifying the impacts of these operational benefits on reliability (EFOR) and commercial availability, we have conservatively estimated the availability benefit during a typical year to be two days over the course of a 365 day year. This 0.55% availability improvement with an average wholesale power price of $40 per mWh equates to approximately $924,000 per year for Limestone 2, net of the fuel costs needed to support the increase in annual output.

2.4.2.4 Mercury

Combined mercury benefits between fuel blending and optimization were 22% as stated above. If this reduction was reflected in proportionally reduced need for activated carbon injection, this would equate to a $5 million dollar annual benefit. If however, we just examine the 5% mercury reduction attributable to optimization, this smaller reduction still equates to an $864,000 annual savings.

2.4.2.5 Limestone Economic Benefits

The operating and cost assumptions as well as the economic benefits achieved at Limestone Unit 2 are shown in Table **4**.

NRG	Limestone Unit 2
Gross Capacity (MW)	913
Net Capacity (MW)	877
Capacity Factor (%)	90%
Annual Output (MWh/y)	6,914,268
Boiler Type	Tangential
Baseline Heat Rate (Btu/kWh)	10,000
Annual Heat Input (mmBtu/yr)	69,142,680
Fuel Cost ($/MMBtu)	$1.50
Eastern/Other Bituminous Coal (%)	0%
PRB/Other Subituminous Coal (%)	50%
Lignite (%)	50%
CO2 Output (tons/yr)	7,372,533
Annual Fuel Cost ($/yr)	$107,971,380
Heat Rate Improvement (-%)	-0.86%
Annual Fuel Savings	**$928,554**
Value of CO2 reduction ($/ton)	$0.00
Annual CO2 Reduction (tons/year)	63,404
Annual CO2 Reduction Benefits	**$0**
Baseline Average Boiler NOx (lb/MMBtu)	0.191
Baseline Annual NOx (tons/yr)	6,862
Average ProcessLink NOx Reduction, at boiler (-%)	-16.00%
SCR/SNCR for Benefits calculations? (Yes/No)	No
Nominal SCR/SNCR-related NOx reduction (%)	0%
Net ProcessLink NOx Reduction, after SCR	0.00%
Average NOx Allowance Credit Value ($/ton)	$750
NOx Reduction Allowance Benefits ($/yr)	**$830,521**
Reagent Cost ($/ton NOx)	$0
NH3 Reduction Value ($/yr)	**$0**
FGD for Benefits calculations? (Yes/No)	Yes
SOx Reduction Allowance Benefits ($/yr)	**$0**
ACI Capital Cost ($/kW)	$20.50
ACI Variable Cost ($/MWh)	$2.50
Total ACI Capital Cost ($)	$18,716,500
Levelized ACI Capital Amortization Cost ($/YR)	$4,854,578
Total Hg Variable Cost ($/MW)	$17,285,670
Average Hg Reduction (%)	5.0%
Annual Hg Benefits	**$864,284**
Annual Availability Increase (%)	0.55%
Increased Availability Value ($/MWh)	$40.00
Increased Availability Value ($/yr)	**$923,832**
Total ProcessLink Suite Savings ($/yr)	**$3,547,190**
Total ProcessLink Suite Savings w CO2 ($/yr)	***$3,547,190***

Table 4: Estimated Efficiency, Emissions, and Availability Benefits for Limestone 2

As reflected in Table 4, the total combined annual benefits for efficiency improvement, NOx reduction, and increased availability is approximately $3.5 million dollars per year.

2.4.2.6 CO_2

Note that while Limestone itself is not yet participating in a liquid CO_2 trading market, many units are about to be affected by the initial auction for the Regional Greenhouse Gas Initiative

(RGGI), some other generators are participating in the Chicago Climate Exchange (CCE), and many others (including Limestone) are in states that have or are in the process of forming other multi-state regional initiatives, such as the Western Climate Initiative and the Midwest Accord. Since there is not yet a mandatory federal cap and trade program for CO_2, and some parts of the two of the three regional accords and several state programs are just getting underway, we did not assign a monetary value for the CO_2 reduction achieved at Limestone 2.

Given the number of state and regional initiatives now in-place or getting underway, however, combined with most observers expecting a federal cap and trade program at some point, it is likely that CO_2 reduction will have a monetary value in the near future. Table 5 below reflects a sensitivity analysis showing the value of CO_2 reduction at Limestone 2 (as a function of the heat rate improvement discussed above) at different $/ton allowance trading prices.

CO2 Price/Ton	Annual Benefit
	-0.86%
$2.50	$158,509
$5.00	$317,019
$7.50	$475,528
$10.00	$634,038
$12.50	$792,547
$15.00	$951,057
$17.50	$1,109,566
$20.00	$1,268,076
$22.50	$1,426,585
$25.00	$1,585,095
$27.50	$1,743,604

Table 5: Potential CO2 Benefits for Limestone 2 as a Function of Allowance Values

As reflected by the numbers in Table 5, the annual dollar benefits for the CO_2 reduction associated with the 0.86% heat rate improvement at Limestone 2 could range anywhere from $158,500 to over $1.7 million per year. It should be pointed out that while operating regional and voluntary CO_2 allowance trading markets have typically traded in the mid-single-digits, CO_2 allowance prices for the well-established EU market in Europe have often traded in the mid-twenties.

2.4.2.7 Economic Benefits as Applied to US Fossil Generation

The benefits achieved at Limestone were extrapolated to the US fossil generation industry, as shown in Table 6, which uses values from a variety of sources: capacity and capacity factors from the 2005 UDI North American Fossil Generation data base; baseline NOx values and SCR and FDG installations from Mclvaine Company; and baseline heat rate and fuel costs based on observations in the field.

Note that the oil and gas category includes both traditional steam turbine units as well as combined cycle plants. Neither SootOpt nor CombustionOpt were assumed to be included in the analysis of benefits as applied to combined cycle units, and SootOpt was not included in oil or gas-fired units. The 0.86% aggregate heat rate improvement gain demonstrated at Limestone was used for all unit types but could be considered a conservative estimate for the following reasons:

1) NeuCo's experience applying CombustionOpt to oil and/or gas-fired units has consistently demonstrated larger benefits;

2) The complexities and interdependencies inherent to a combined cycle unit are such that NeuCo and its partners with domain expertise in combined cycle operations believe that heat rate gains for PerformanceOpt and MaintenanceOpt for these types of plants will likely be well in excess of one percent.

US Fossil Units	Typical PRB W/SCR	Typical PRB No/SCR	Typical Bitum W/SCR	Typical Bitum No/SCR	Oil/Gas (ST + CCCT)	Total (1950 Units) Industry Benefits
Gross Capacity (MW)	698	246	698	246	198	514,359
Net Capacity (MW)	645	227	645	228	192	475,782
Capacity Factor (%)	90%	80%	90%	80.0%	40.0%	82.7%
Annual Output (MWh/y)	5,089,038	1,592,075	5,089,038	1,594,670	672,768	3,446,769,199
Baseline Heat Rate (Btu/kWh)	10,000	10,000	10,000	10,000	10,000	10,000
Annual Heat Input (mmBtu/yr)	50,890,382	15,920,747	50,890,382	15,946,704	6,727,680	34,467,691,992
Fuel Cost ($/MMBtu)	$1.50	$1.50	$2.50	$2.50	$6.00	$2.19
CO2 Output (tons/yr)	7,683,450	2,403,721	5,382,637	1,686,671	1,076,429	6,379,454,175
Annual Fuel Cost ($/yr)	$82,524,944	$25,817,428	$137,541,573	$43,099,200	$40,366,080	$75,546,189,528
Heat Rate Improvement (-%)	-0.86%	-0.86%	-0.86%	-0.86%	-0.86%	-0.86%
Annual Fuel Savings	$709,715	$222,030	$1,182,858	$370,653	$347,148	$649,697,230
Value of CO2 reduction ($/ton)	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
Annual CO2 Reduction (tons/year)	71,435	22,348	50,044	15,681	9,257	54,863,306
Annual CO2 Reduction Benefits	$0	$0	$0	$0	$0	$0
Baseline Average Boiler NOx (lb/MMBtu)	0.25	0.20	0.30	0.28	0.25	0.27
Baseline Annual NOx (tons/yr)	6,877	1,721	8,252	2,370	865	4,942,773
Avg ProcessLink NOx Reduction, at boiler (-%)	-16.00%	-16.00%	-16.00%	-16.00%	-16.00%	-16.00%
NH3 Reduction (%)	-14.40%	0.00%	-14.40%	0.00%	0.00%	-14.40%
Average NOx Allowance Credit Value ($/ton)	$1,844	$1,844	$1,844	$1,844	$1,844	$1,844
NOx Reduction Allowance Benefits ($/yr)	$38,512	$507,743	$46,214	$699,285	$255,241	$183,420,330
NH3 Cost ($/ton NOx)	$350	$350	$350	$350	$0	$350
NH3 Reduction Value ($/yr)	$346,605	$0	$462,140	$0	$0	$181,001,022
SOx Reduction Allowance Benefits ($/yr)	$53,938	$16,874	$165,600	$51,891	$11,065	$40,511,589
Annual Availability Increase (%)	0.55%	0.55%	0.55%	0.55%	0.55%	0.55%
Increased Availability Value ($/MWh)	$45.00	$50.00	$45.00	$50.00	$100.00	$48.77
Increased Availability Value ($/yr)	$805,650	$295,825	$503,058	$201,489	$148,009	$659,012,936
Total ProcessLink Suite Savings ($/yr)	**$1,954,419**	**$1,042,472**	**$2,359,870**	**$1,323,318**	**$761,463**	**$1,713,643,106**

Table 6: Economic Benefits as Applied to US Fossil Generation

As the numbers in Table 6 indicate, the benefits available to the industry based on the results achieved at Limestone are greater than $1.7 billion dollars per year in annual savings across the full combination of unit types, fuel sources, and post-combustion controls characterizing the current US fossil generation fleet. These aggregate benefits are distributed across the categories of fuel efficiency, NOx reduction, reagent costs, CO_2 emissions, and commercial availability. Mercury reduction benefits are not included in this table because they are too site- and fuel-specific in nature for such an aggregate analysis. CO_2 benefits are also not included, since there is no current liquid cap and trade market for the US.

2.4.3 Key Learnings

Following are the key learnings of the project:

- Variability in Hg production/removal does appear to exist as a function of un-modified combustion processes, though in this study the sensitivity was relatively weak.
- Reliable Hg CEMS do exist and appear to provide sufficiently good data for analysis and optimization of upstream processes. In fact the use of inductive methods against these signals can most likely support Hg optimization product development when regulatory and market conditions support it.
- Mercury removal and total emissions VOA's can be developed to provide useful analysis in the middle range of acuity, sufficient for assessing medium and long term response characteristics and integrating those responses into a wider KPI matrix.

- Significant benefit is provided by the availability of an integrated platform upon which to bring the wide variety of data management and analytics approaches: first principles, adaptive and expert system based modeling technologies, optimization and anomaly detection engines, and rapid prototyping of distributable applications. In short, the ProcessLink platform, or platforms like it, is essential to making the application of advanced optimization technology beneficial and cost effective.
- Advanced instrumentation must be reliable, robust and cost effective to have significant utility in a real production setting. Each form of instrumentation needs to be weighed against its likely reliability, ease and cost of maintenance, the degree to which it has to scale to be useful, and the value of the information it provides for optimization applications.
- The vast majority of data, and the knowledge it contains, along with control and optimization opportunity, goes un-examined and un-used. Significant opportunity already exists within existing under-utilized reservoirs of knowledge, hidden in raw data. Wider utilization of on-line analytic approaches, including but not limited to modeling and optimization will likely bear cost-effective fruit.
- Regulation and market variability and uncertainty are major obstacles to progress in developing the benefits because they define the value of optimization opportunity that exists. Optimization can help when objectives are fluid, but a cost gradient must be well-enough defined to justify the cost of applying the technology and provide context when managing tradeoffs.
- Information technology has an essential role to play in capitalizing on the opportunities that exist and meeting the challenges of a shrinking workforce, an aging fleet, the rapid approach of new technology and the exponential increase in the complexity of production context. The evolving security landscape must continue to embrace and support this.

2.4.4 Conclusions

The benefits shown over the course of the project represent real bottom line value. The fact that all objective dimensions saw some improvement is strong evidence of the value of optimization technologies. Moreover, the benefits that were seen were significant, especially where relevant to the host site’s priorities: LMS U2 goals included reducing NOx emissions and improving heat rate.

Because of Limestone’s use of Lignite coal, fuel blending to include more PRB coal was the largest driver of Mercury improvement on this particular unit. Lignite has higher levels of Mercury than PRB, so the Mercury reductions provided by changing to a higher ratio of PRB are to be expected. Lignite is currently not a typical fuel for units in the US fleet however, and fuel blending, despite the numerous other benefits it can provide, is not always possible or justifiable in other dimensions. However, fuel blending was the largest driver of Mercury performance on this particular unit, and a critical factor in the success of this project.

Optimization, in addition to the direct, though modest benefits it provided in terms of Mercury performance, also played a role in getting the best performance from the unit under conditions where something as fundamental as fuel blend is changing dramatically, where constraints and objectives compete, and relationships driving final outcomes are not well known.

The Mercury CEMS installed at the ESP Inlet, FGD Inlet and FGD Outlet proved to be extremely challenging to maintain. The instruments used were not sufficiently hardened for the hostile conditions found in the required locations. The maintenance reserve of spare parts lasted a fraction of the expected duration and significant cost was added in an effort to keep them running. The air-conditioning system was found to be under-sized for the heat of Texas in the summer and the cabinets were not sufficient for extremely wet and windy conditions found at other times of the year. In the end, despite added cost for maintenance visits, remote support, spare parts, and good faith efforts on the part of the vendor, PSA, the amount of Mercury data taken from around the ESP and FGD was smaller than expected. Furthermore, analysis showed that even when data was coming in it was not always of usable value, presenting inconsistent or infeasible results that could not be reconciled with other indications. Calibration drift and hardware failure were the most frequent culprits. The installation of an additional analyzer in the existing CEMS containment relatively late in the project, and on the plant's initiative, provided the majority of useful data.

The future regulation of Mercury emissions is uncertain and changed significantly over the course of the project. However, it is generally expected to increase in stringency. The most likely instrumentation scenario is one where Stack based Hg CEMS, like the one more recently installed by the plant, will be used to report against those regulations. The project analysis suggests that this kind of instrumentation supports some opportunity for reducing Mercury emissions through the optimization of standard upstream processes, similar to NOx, CO and Opacity. Since the post combustion removal technologies for Mercury are only now being deployed on commercial scale and have unknown tradeoffs and impact with other systems and processes, it is likely that optimization can play a role in helping to achieve the fastest possible path to effective utilization of those systems, while minimizing other impacts.

At the end of Phase II an analysis of Mercury data gathered up to that point was conducted. Table 7 shows the resulting scenarios that provided a basis for expected reductions due to the most important optimization variables. One of the most important results is that the sensitivities shown are essentially identical to those for NOx.

Because earlier estimates showed a correlation between NOx and Hg reduction, and most importantly because a reliable Hg signal was extremely elusive, only a small portion of time in the fall of 2009 saw Hg removal added as a direct optimization goal. In the end it took painstaking hand-cleaning of Mercury data to create a usable VOA, a process that could not be feasibly automated in real-time. Given this, it was a helpful result at the end of Phase II to find that the Hg data that had been collected at the time showed that NOx appeared as a good proxy for Mercury in a way that was sufficient, given the challenges of aiming at intermittent and drifting Mercury signals. The sensitivities of the Hg VOAs call this initial observation into question and suggest that in the future Hg signals will have to be represented independently in the optimizer's goals, and may compete with NOx.

Scenario	O2 Setpoint	Tilts	Mercury Removal (Percent)	Percent Reduction
Baseline	2.4	62.5	35	-
Lower Tilts	2.4	50	39	6
Lower O2	2.0	62.5	41.5	8
Lower Tilts and O2	2.0	50	48	20

Table 7: Expected results in Hg Removal based on Phase II analysis

The analysis carried out here however showed a reduction of emissions of around 5% percent, due strictly to non-fuel related optimization. This was despite the fact that significant differences were seen in O2 and tilts. More puzzling, the VOA models showed inverted and weaker sensitivity to O2 than the earlier analysis suggested. One possible reason is that the dynamic control of O2 exercised by the Model Predictive Controller (MPC) to keep CO in check, disrupted the process responsible for the earlier results, or masked the positive correlation to removal seen previously. Another is that the neural model VOAs attenuated the sensitivity, something that is typically desirable in a neural model, when confidence in sensitivity may not be high. This would lead to reduced deltas relative to actual. More consistent high quality Hg emissions data, even if it is only at the stack may provide better resolution of sensitivities and show that the earlier estimates were realistic.

The advanced instrumentation outlay initially envisioned for the project was ambitious. A variety of factors affected the final utility of the instruments involved, many of which were almost entirely specific to the unit involved, and/or its lignite fuel. Different pieces of information have different value depending on any given production context. An instrument that may have shown low utility or reliability on one site may turn out to be mission critical at another. However all instrumentation brings significant cost and must be weighed as such against final value in its context. In addition, the use of advanced instrumentation clearly benefits from analysis, integrating the information it provides with other sources, cross-validating, and dissecting each other to create a more comprehensive picture of a complex process.

The unstable regulatory and economic climate has a significant effect on production steering. The goals that represent achievable bottom-line value are determined by the market. At present, due to both the general state of the economy and the political and regulatory environment, the market for NOx and SOx allowances is weak, and the abdication of CAMR is affecting the choices power producers make regarding future Mercury emissions regulations.

Many acknowledge that money and time not spent now will most likely have to be spent later. But neither can be spent without more concrete justification. Because this climate is so multidimensional and variable, production steering, the management choices producers make to intersect desired future outcomes, is more or less synonymous with optimization. In this sense optimization has a big role to play at the tactical and strategic levels, not just in the real-time control domain.

Optimization technology also has a cost. However, the benefits have been shown to justify that cost. An overall increase in the involvement of the right strata of plant personnel and to some degree increasing presence in operation management of analytics would improve the degree to which benefits of the type shown here can be realized. This is all the more important given the amount of large-scale change to numerous aspects of the production and market landscape that can reasonably be expected in the coming years. Statistical methods, systems analysis, modeling and optimization are not the typical skill set of today's plant performance or control engineers, but are increasingly in need as today's power plant becomes an increasingly complex aggregation of technologies, subject to increasingly dynamic objectives and constraints, all represented in data.

3 Experimental

This section covers the major deliverables of project work. It includes a description of the IT component, without which the project could not have been carried out; discusses the systems that were evaluated and deployed; covers the acquisition of Mercury data and the development of the Mercury VOA's; and uses multiple methods to examine the benefits delivered.

3.1 Data Integration

3.1.1 LAN Map

Data integration for the project had to tie together a wide variety of data systems. These included the plant Distributed Control System (DCS) responsible for controlling combustion and balance of plant processes, the distributed non-DCS control systems, such as those supporting the sootblowing and ESP systems, and the variety of data systems supporting the instrumentation installed for the project. In its final form the data collection consisted of more than half a dozen significant and distinct data streams and leveraged OPC interfaces proprietary to the plant DCS. Over the course of the project the architecture evolved to fit ProcessLink's distributed data collection model and include newer, more-powerful hardware.

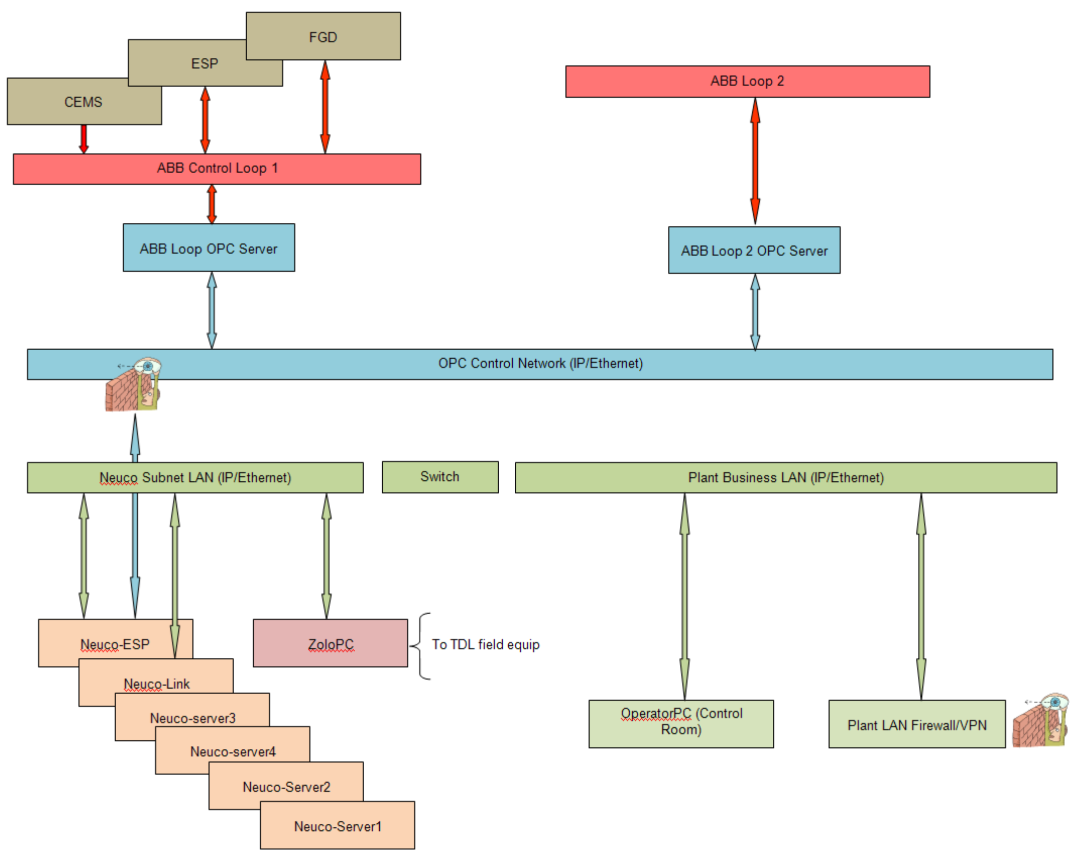

Figure 5: LAN Map

One key aspect of the architecture is that it had to support remote access for NeuCo application engineers and developers. The amount of work needed to build and support a plant wide optimization system of this scope had to include remote access in order to be cost effective and logistically feasible.

Another key aspect is that it had to support closed-loop supervisory optimization of plant processes.

3.1.2 Closed-Loop Integration

Closed –loop integration is critical to the success of supervisory optimization systems, especially where system complexity and dimensionality is high, and inductive methods are used. High dimensionality systems need to be subjected to machine-like manipulation in order for significant resolution of response characteristics to be achieved. High complexity, high dimensionality also implies that relatively high frequency of control is needed in order to achieve meaningful control effect. For this reason optimization systems are typically not deployed with an open-loop step. Instead direct search and analytic procedures are used to “seed” machine learning, which is then carried out in closed-loop by the machine, or expert rules are derived that sufficiently mimic operator actions. Machine-process interaction is then analyzed in real-time and adjusted iteratively to achieve and validate control and optimization.

Closed-loop control where control boundaries are crossed requires significant consideration of failure modes as part of its design. Important aspects of the methods used to achieve closed loop control of combustion optimization and sootblowing optimization are described below in Section 3.3.4.

3.1.3 Response to Evolution of NERC Guidelines

Over the course of the project the NERC standards became a significant input to system architecture as concerns over cyber security around critical national assets had begun to be addressed by government and industry. Currently the response to NERC guidelines, which leave significant room for interpretation, varies widely from plant to plant, and features a spectrum of approaches and philosophies.

Some strategies that are currently being used to accommodate NERC guidelines include the layering of fire-walls between the outside world and critical control systems. Over the course of the project significant work was undertaken to provide support for these network designs in ProcessLink’s distributed client-server architecture.

3.2 Evaluated Systems

This section reviews each of the systems that were evaluated , but for one reason or another were not deployed. An explanation of the reason the evaluation did not support further development (at the time) of the system has been given in each case.

3.2.1 Advanced Electrostatic Precipitator (ESP) Optimization System

The ESP Optimization System is composed of a Carbon-In-Ash (CIA) virtual online analyzer, a CIA sensor from ABB, and ESP Optimization software.

Despite a relative lack of issues with the install and solid operation during the first half of Phase II, the ABB CIA instruments failed at the end of Phase II due to mirror erosion. Support for this instrument was discontinued by ABB shortly thereafter and replacement parts were not available. The loss of the CIA instrument and lack of vendor support have reduced the degree to which

CIA can be directly correlated with ESP Hg oxidation (the primary effect the ESP has on the Hg removal process).

In the process of learning more about the ESP system at LMS U2, it was found that a power optimization system had been installed. The optimization system was used to control the overall power consumed in the ESP by monitoring the opacity in the stack. As the opacity increased, the overall power in the ESP was increased. As the opacity decreased, the overall power was decreased. In addition, as described in Section 3.4 on mercury removal, it was found that there was negligible mercury removal in the ESP. Because the unit already had a power optimization system, and also because no mercury was removed in the ESP, it was determined that there was no additional benefit available for enhancing the currently-used ESP power optimization system. For this reason, no advanced ESP optimization system was implemented.

3.2.2 Advanced Flue Gas Desulfurization (FGD) Optimization System

The LMS U2 FGD underwent a major revision to produce gypsum as a byproduct instead of calcium sulfite. The revamped FGD upgrade was completed in February 2009 (early in Phase III) but startup issues persisted into June, preventing any parametric operation or optimization of the FGD during a period of time when it (later) turned out good Hg removal data was available.

During Phase II we also encountered changes in the regulatory context (Clean Air Interstate Rule - CAIR) as well as the economy as a whole that dramatically affected SO2 credit prices. The low cost of these SO2 credits strongly undermined the value proposition of an FGD optimization product.

The original plan for optimization of the FGD system had been to increase the SO2 removal while taking into consideration the cost of SO2 credits to LMS U2. Later, after the FGD upgrade, the goal was changed to increase SO2 removal while minimally impacting the gypsum byproduct. However, by the summer of 2009, the SO2 credit prices had dropped so much that the operator was no longer interested in increasing SO2; rather they were interested in minimizing cost. This was accomplished primarily by bypassing flue gas around the FGDs. Minimizing cost is this manner is simple and required no optimization system. For this reason, the effort to implement an FGD optimization system was abandoned.

Further, an analysis of the role that FGD operating profile plays in Hg removal concluded that under the current operating conditions, as dictated by the SO2 credit market, there is little operating data to support an analysis of scrubber profile specific effects at this time. The analysis also showed that the interaction between as-found (fixed operating point) scrubber conditions and combustion and optimization actions taken by the combustion and sootblowing specific systems were still of high interest since most Hg removal is occurring, as expected, in the FGD.

3.2.3 High Fidelity Simulator

During Phase II of the project the host site deployed a control room simulator for operator training and the screens the operators used to control the CombustionOpt® system were included in that simulation. However, after technical discussions with the Control Simulator vendor (Invensys) it was determined that there would be little value, in terms of duplicating operator experience with an active optimizer in such a simulated setting because optimization is fundamentally context specific. Any set of scenarios simulated deterministically, and at significant cost, would have only minimal relevance to the operators' understanding of optimizer function and how to interact with it. It was determined that operator training, both with respect to the principles of optimization as well as the analysis tools provided as part of the closed-loop systems, would be the most effective way to achieve the site's goals for operator training.

3.3 Deployed Systems

This section reviews each of the deployed systems. Each review provides a summary of how the system fared over the course of the project, to what degree it turned out to be useful, and the challenges that were encountered.

3.3.1 Intelligent Fuel Management System (FMS)

The Intelligent Fuel Management System (FMS) is composed of the Ready Engineering Coal Fusion System, Sabia's elemental analyzer, and NeuCo's CombustionOpt optimization product.

The Ready Engineering Coal Fusion system allows LMS U2 coal management staff to control the ratio of lignite to PRB fuel to a setpoint with reasonable accuracy.

The deployment of the Coal Fusion system was largely completed during Phase I though some problems remained into Phase II.

The Ready Engineering system has operated in closed-loop since the fall of 2008, when issues including mine mouth equipment capacity and control were resolved at some expense over and above those funds budgeted. This system uses linear programming, customized to the coal transport hardware at LMS U2 to blend lignite coal with western coal (PRB) to a specification in percent PRB. This system, though not without obstacles, was seen as a boon by the plant early on, for reasons that are not limited to Hg and NOx control. It played a critical role in providing the results seen in Hg emissions reduction. Utilization of this system continues to be at 85% or higher and the plant is generally satisfied.

The Sabia coal analyzer was a relatively straightforward installation and has not presented maintenance challenges per se, however, it has shown in this analysis to be susceptible to substantial drift unless routine calibration is done. Because of the way the operators tend to use this signal, adjusting the PRB blend up when they see total Btu content of the blend dip excessively, its long term value is not as important as its effectiveness at telling the operators whether the coal the next shift will use is substantially lower in Btu content than what is being used in the current shift. This gives the operators a window of about eight hours to react. Sweetening the blend in such situations reduces the duration and severity of bad-coal-induced operational headaches.

Figure 6: Sabia On-Belt Coal Analyzer

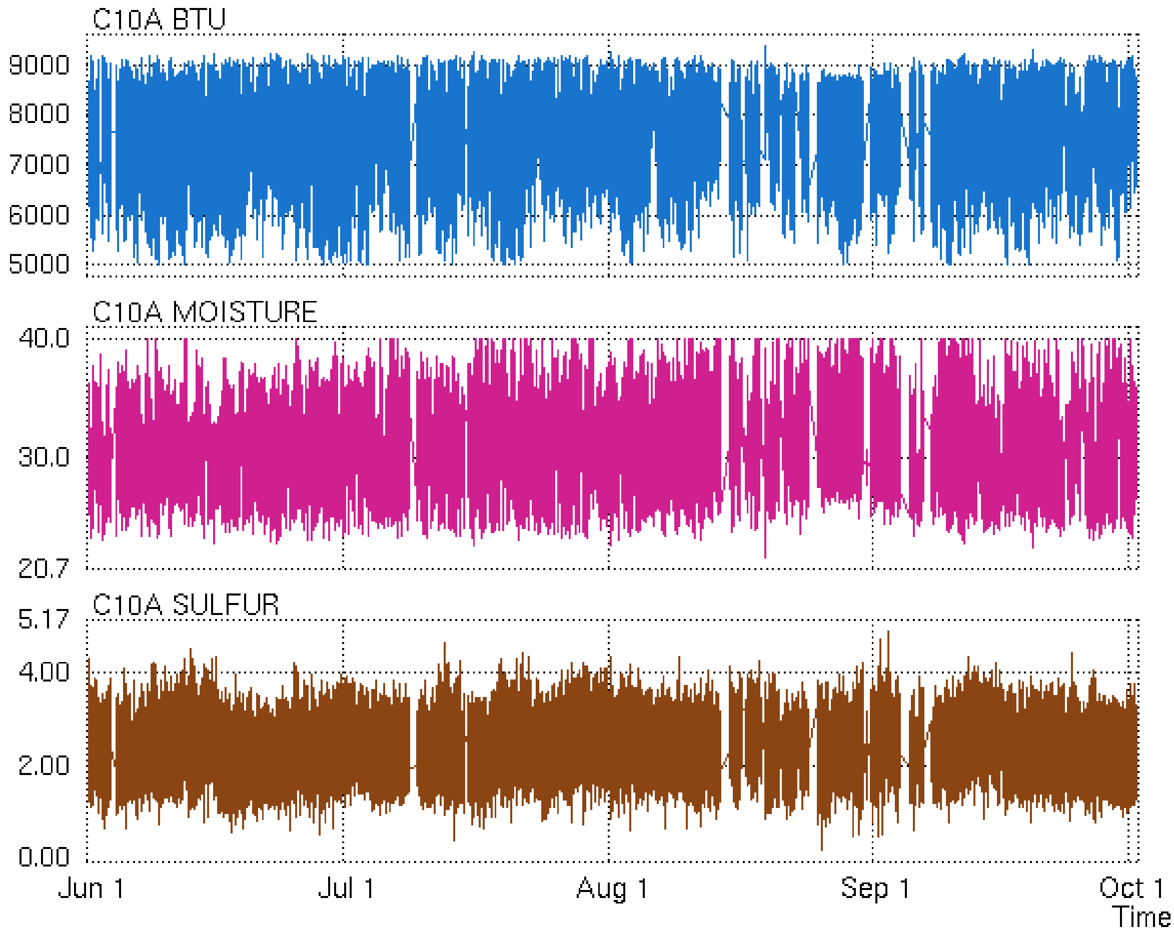

Figure 7: Data Samples Collected From the Sabia Analyzer

The data presented in Figure 7, which were collected over a five-month period, include coal BTU content, moisture and sulfur content.

The importance of both the Coal Fusion system and Sabia analyzer, and the relative cost-effectiveness of the instruments in this particular project, were very high.

3.3.2 Advanced Intelligent Sootblowing (ISB) System (SootOpt)

The ISB system is composed of the SootOpt intelligent sootblowing software. Note that this module was previously demonstrated, and does not constitute new demonstration technology, although certain advances were made.

SootOpt models the effect of soot blowing activity on heat transfer throughout the furnace and backpass and dynamically determines the optimal boiler cleaning actions to improve availability, heat rate and emissions performance. It works in conjunction with existing sootblowing controls to drive closed-loop actions that avoid boiler zone over- or under-cleaning.

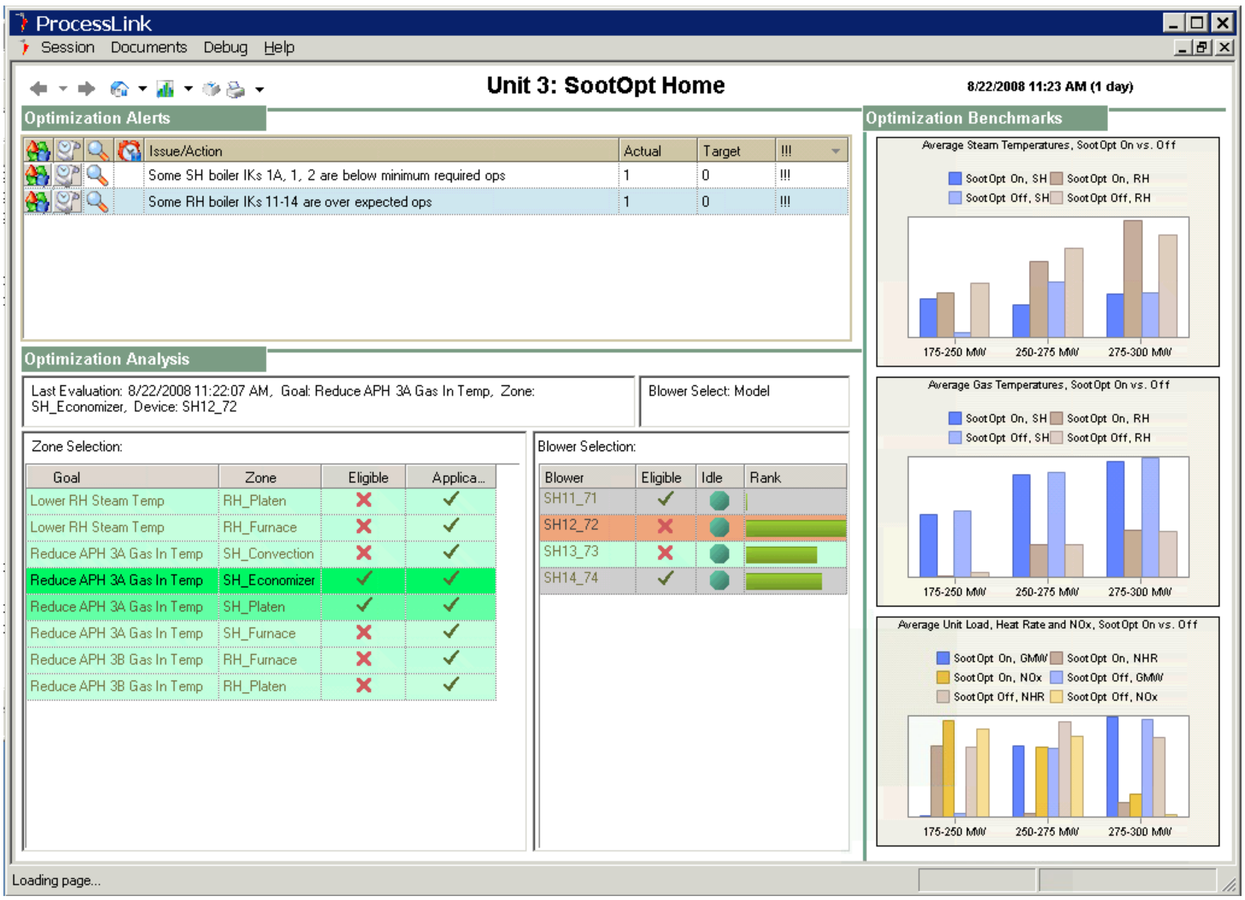

Figure 8: SootOpt Home Page

The SootOpt closed-loop optimizer is currently running with moderate utilization. Rules have stabilized at this time and its goals have been integrated with those set for the MPC and neural combustion optimizers.

The primary obstacle to getting higher rates of utilization centers around the long, retractable, sootblowers (IK's) that clean the Platen and DivWall SH sections. These particular blowers have a dramatic effect on unit performance but have been kept under operator control to date.

3.3.3 Mercury Specie Control System

The Mercury Specie Control System includes the boiler area optimization, sensors from Zolo Technologies, PS Analytical, and Tekran with mercury emissions being measured through Continuous Emission Monitors (CEMS) by PS Analytical (PSA) and Tekran.

The instrumentation from Zolo and PSA was installed roughly on schedule in Phase I. However, the PSA instrument suffered numerous issues that continued into Phase II and on into the Demonstration period. The Tekran stack Hg CEMS was not part of the project but was installed by the plant in Phase III and came on-line in early 2009. It helped to fill the gap left by the chronically-ailing PSA CEMS. The boiler area optimizer was installed roughly on schedule in Phase II and went into closed-loop service in the fall of 2008, with utilization increasing. Each of these systems is discussed in this section. The Zolo instrument package and CombustionOpt are discussed first, followed by the Mercury CEMS, including detail of data collection and VOA development.

Hg data collection using the Stack-based Tekran CEMS was discontinued on December 31, 2009. The decision to stop measuring Hg prior to the end of the project was based largely on a change in the regulatory context for Mercury emissions (vacating of CAMR). Although this decision related to the Stack Hg CEMS specifically, it was also decided to decommission the PSA instruments at that time due to the high cost of maintaining the PSA instruments and the non-working status of the FGD Outlet instrument which had been functionally replaced by the Stack measurement. The consensus was that sufficient data had been collected to support a meaningful analysis, and that the amount of additional expenditure that would be needed to restore the PSA CEMS to its best form could not be justified.

3.3.3.1 Zolo Sensors

The Zolo laser sensors, which provide real-time information indicating species compositions and temperatures directly within the combustion zone, were installed in Phase I. Because LMS U2 is a double furnace t-fired unit with a dividing wall between the two furnaces, the typical cross-firing Tunable Diode Laser (“TDL”) array could not be installed. Still the four crossing lasers per furnace were expected to provide useful data. However, this was the first unit burning lignite coal on which Zolo’s TDL had been tested and it is also a particularly wide furnace. Due to high ash content, the signals were intermittent despite the vendor’s consistent efforts. To make matters worse the unit suffered from slagging issues, which were especially severe given the high ash content of lignite fuel and which caused the view ports to plug up causing loss of signal. In order to overcome the slagging issue, longer port rodders, devices that are periodically inserted through the view port to clear it out, were installed during Phase II. However, just as they came on-line a series of unavoidable IT issues prevented integration of the new, more consistent data into the real-time optimization. Vendor engineers also developed a redesigned port based on experience at other sites where high slagging rates cause excessive wear on port rodders. Site staff recevied these designs but wanted to wait with any modifications until the change to higher PRB blend at the end of 2009. Current plans are to make the specified alterations during the next major outage.

Despite the fact that these instruments were not able to play a strong role in the optimization or analysis, the expectation of future utility is very high and has been demonstrated on a number of other sites. Zolo provided data for the period of analysis (taken from their data collector) but time constraints prevented its integration.

3.3.3.2 Combustion Optimization System (CombustionOpt)

CombustionOpt uses neural networks, model predictive control (MPC) and other technologies to extract knowledge about the combustion process and determine the optimal balance of fuel and air mixing in the furnace. It optimizes fuel-to-air ratios in real-time by biasing DCS set-points to adjust dampers, burner tilts, pulverizer settings, over-fire air and other controllable parameters to their optimal levels for a given set of conditions, objectives and constraints.

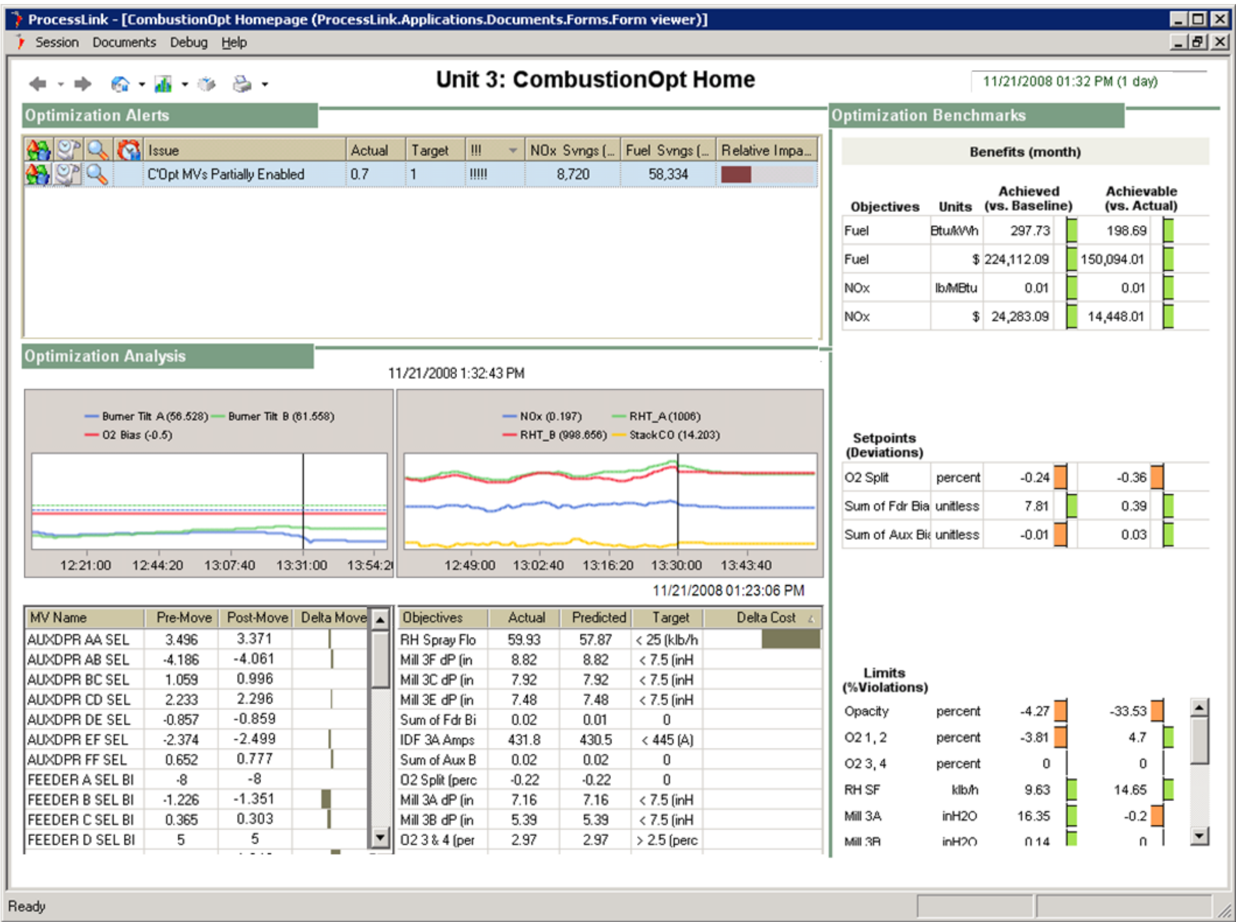

Figure 9: CombustionOpt Home Page

CombustionOpt was installed at LMS U2 in Phase II, went through direct search testing in the fall of 2008 and then began sustained closed-loop optimization working on NOx, CO, O2 and Tilt RH Temperatures.

Mercury was added as a direct optimization objective in the early fall of 2009, in Phase III. It was added in the form of a “down” objective for the neural optimizer, looking at the Tekran Stack Hg CEMS that had only then come on-line in closed loop (prior data was supplied after the fact from the Tekran data logger). Based on analysis done to date however, it was expected that Hg emission reductions, and removal improvements would be coincident with NOx reductions. NOx was a significant priority for LMS U2.

3.3.4 Intelligent Plant Optimization

The NeuCo I-Plant Optimization consists of BoilerOpt™, which ties together the optimization of the combustion and heat transfer processes, as well as PerformanceOpt® and MaintenanceOpt®, which measure unit performance and provide early detection of operating and equipment problems.

3.3.4.1 BoilerOpt

BoilerOpt consists of the integration of the combustion and sootblowing optimization systems (CombustionOpt and SootOpt). This integration scheme, which can be seen in Figure 10, leverages the non-adaptive features of the MPC technology to manage the large critical and dynamic controls first. The adaptive power of neural model-based optimization and expert rules are then used to support this activity, reacting when the Controller becomes constrained, and searching the large number of control dimensions for usable impact.

MPC consists of a set of fixed relationships between large control manipulated variables (MV’s) and objectives. These relationships can be adaptively developed but significant expectations exist about what they should look like when found. In many cases a good guess based on similar units is enough to get started and there is no inherent dependency on regression methods (like neural nets), which by definition bring error. Neural technology is then used to search the large number of secondary control response relationships, such as the NOx response to the settings of ten individual auxiliary air dampers, for useful sensitivity, which may or may not exist, and which when found, is hard to qualify without just giving it a try.

SootOpt then uses expert system rules based on experience that can be written down and qualified to consistently take the cleaning actions that support goals it shares with both the MPC and neural optimizer. However its actions are more designed to reduce the constraints on either system imposed by a distorted or degraded heat transfer profile.

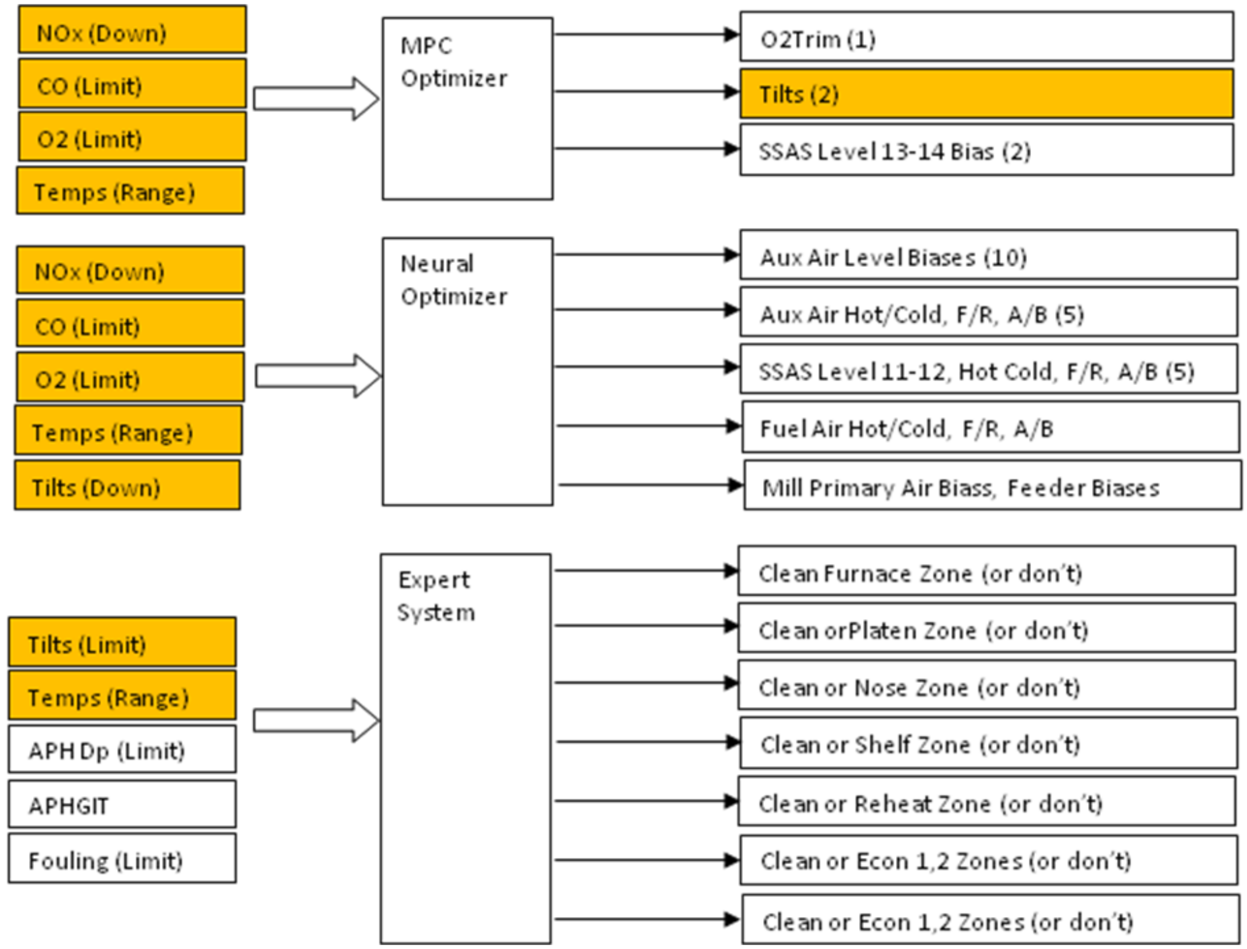

Figure 10: BoilerOpt Integrated Optimization Scheme

3.3.4.2 PerformanceOpt and MaintenanceOpt

PerformanceOpt is a real-time proactive performance management system. It continuously monitors thermal performance, alerts users to unit efficiency and capacity degradation and provides the contextual data to efficiently diagnose unit-wide performance issues. PerformanceOpt notifies the user when it finds potential opportunities to improve efficiency or capacity or when there are significant changes in the way the unit is performing.

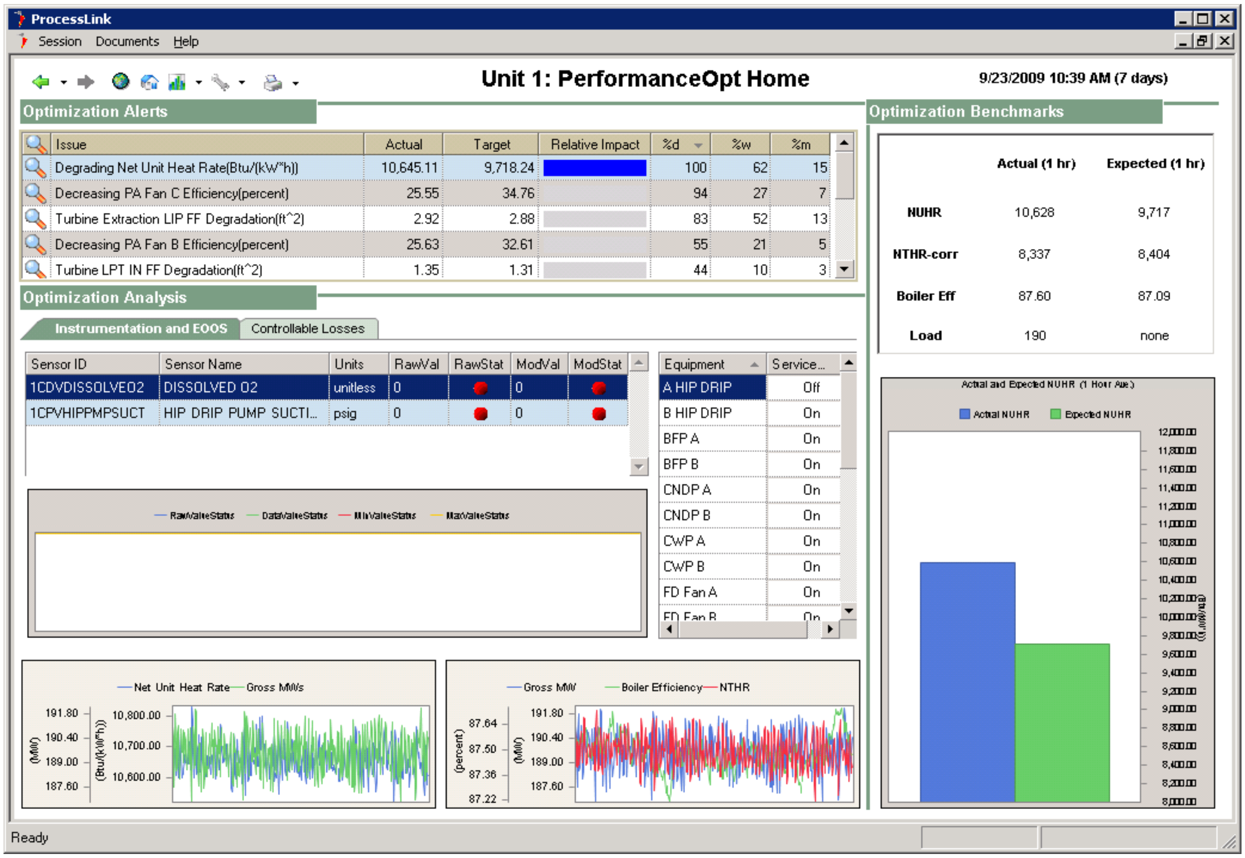

Figure 11: PerformanceOpt Home Page

Figure 12 and Figure 13 show a good match between Zolo Furnace Exit Gas Temperature (FEGT) and PerformanceOpt model-predicted FEGT as well as Sabia Fuel Higher Heating Value (HHV) and PerformanceOpt model estimated HHV. There are numerous ways of making good use of these relationships, cross validation of models and instruments being just one.

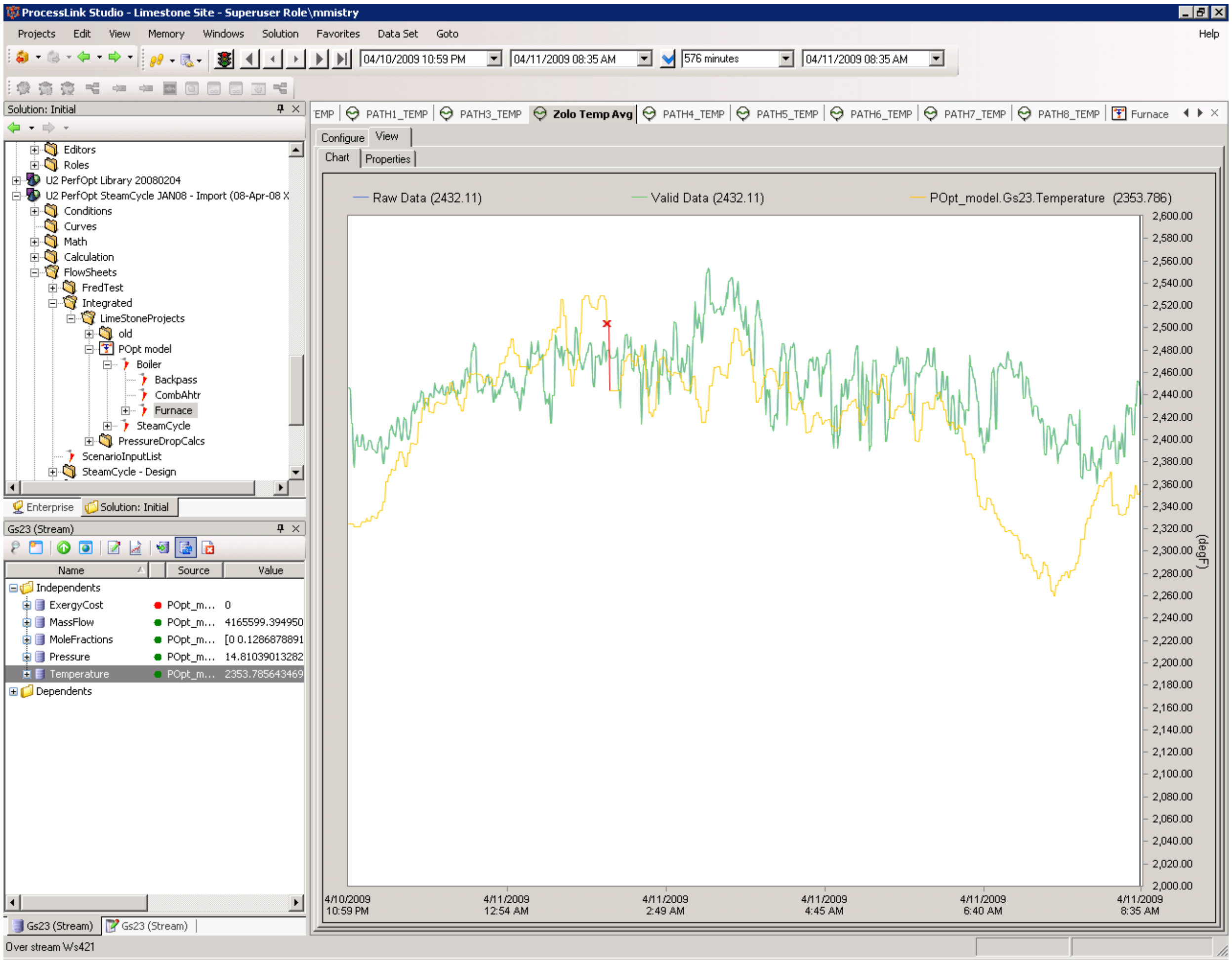

Figure 12: Zolo Measured FEGT (Green) vs. PerformanceOpt Model Predicted FEGT (Yellow)

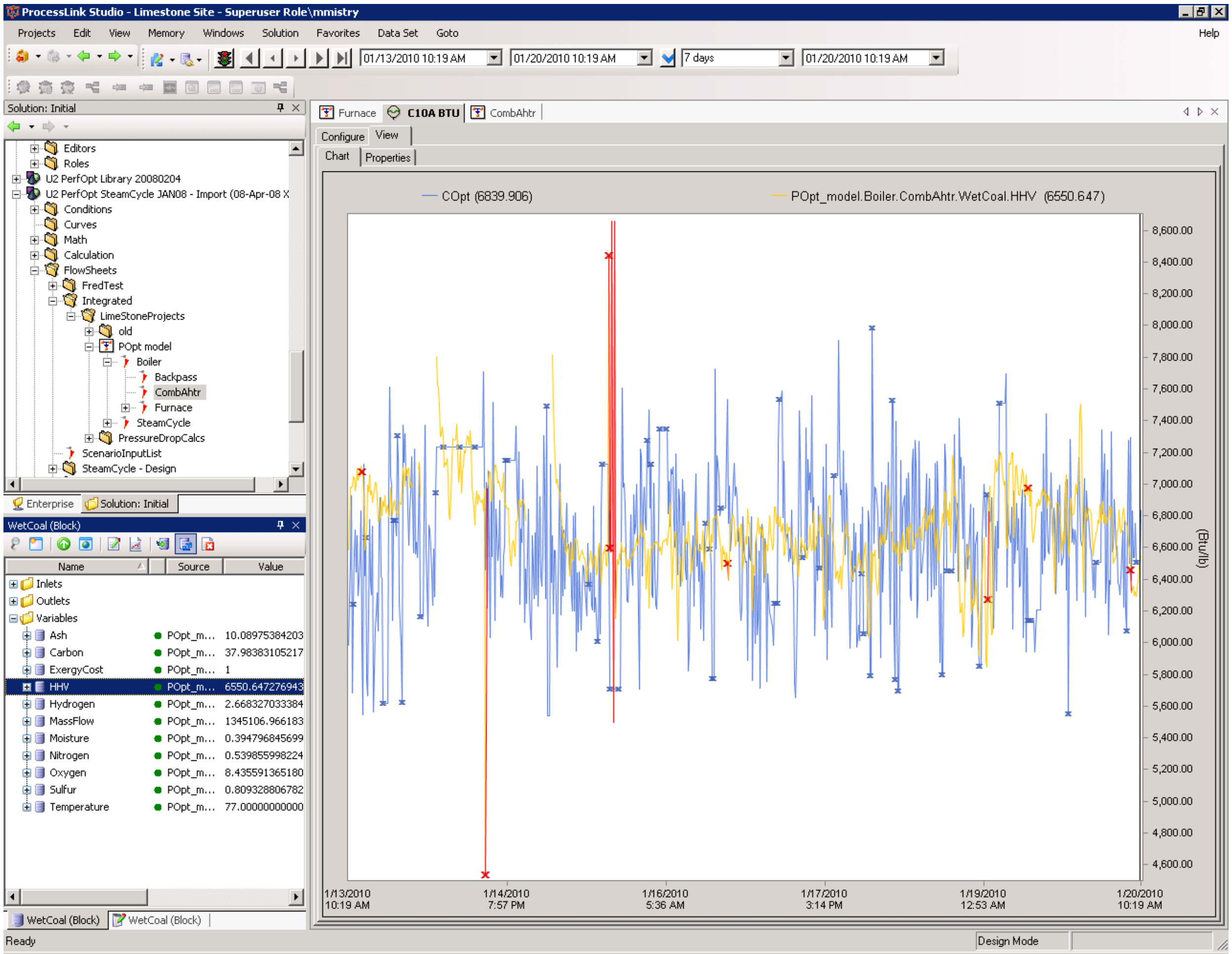

Figure 13: Sabia HHV vs. PerformanceOpt HHV

MaintenanceOpt employs adaptive neural network models that monitor plant data in real-time, constantly searching for anomalies that point to equipment health problems. The system predicts expected values for signals under current operating conditions, compares them to actual values, and, when the difference between the predicted and actual values exceeds an appropriate threshold, generates an alert to notify users of a potential equipment problem. MaintenanceOpt's embedded diagnostic support system provides users with all relevant historical and real-time contextual data, models of expected performance, and a list of potential causes and corrective actions. MaintenanceOpt streamlines the entire lifecycle by which equipment health issues go from detection to resolution, saving valuable time.

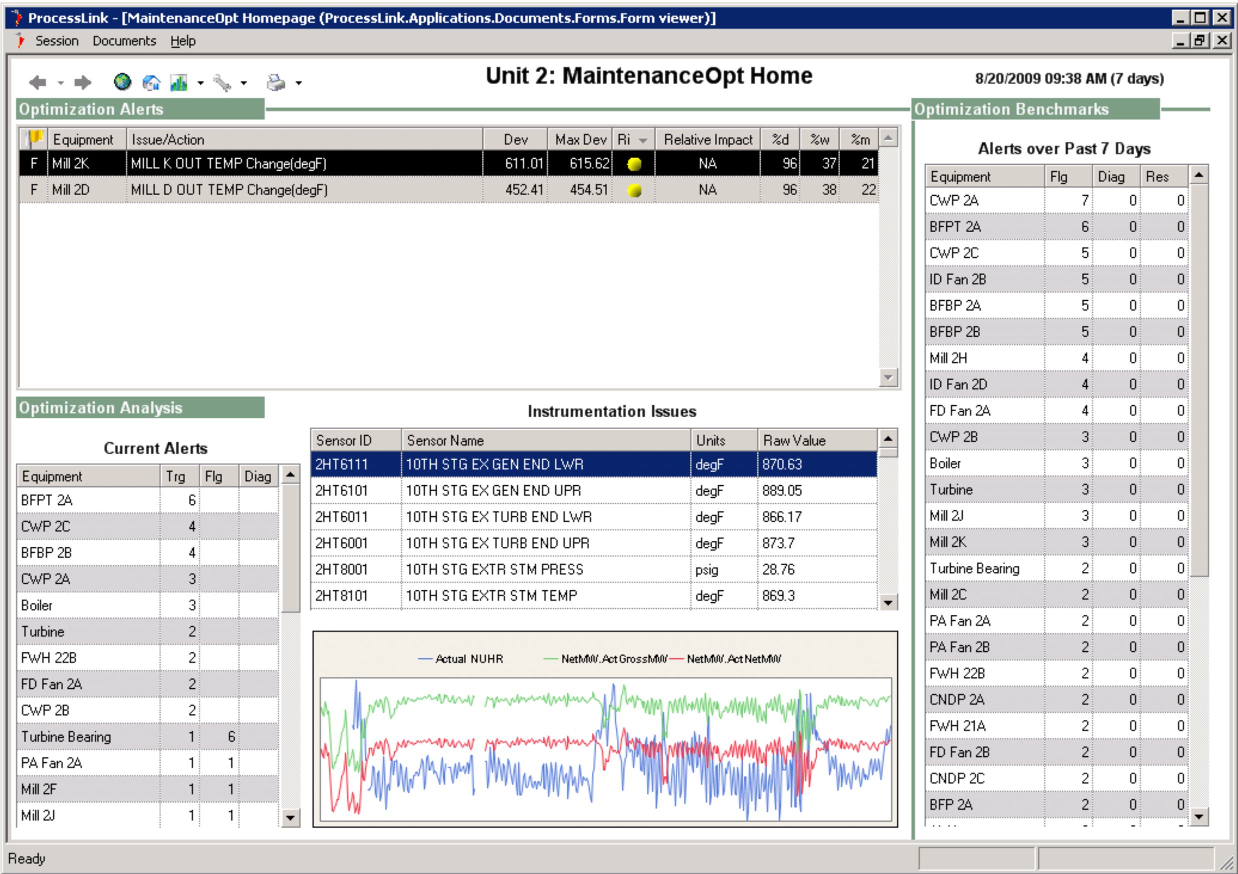

Figure 14: MaintenanceOpt Home Page

Since installation, both PerformanceOpt and MaintenanceOpt have been alerting the plant to performance and equipment health anomalies that need attention. Although the quantity of alerts varies, on a typical day PerformanceOpt and MaintenanceOpt will generate between five and ten alerts for LMS U2. These alerts have been for a variety of issues and symptoms including main turbine bearing vibrations, economizer gas outlet temperature stratification, boiler feed pump turbine HP temperature, primary air fan bearing temperature, and feedwater heater drain cooler approach issues.

To gain more insight into the value that these alerts provide, following is an example of the process undertaken around an alert that MaintenanceOpt generated for a primary air fan. The LMS U2 user who was reviewing the alerts saw that a primary air fan bearing was at 174 degrees while its expected temperature was 150 degrees. By clicking on the triggered condition's context data charts, the user saw an expanded view of the history of the trigger and the actual temperatures for all bearings on that fan. Only the temperature of the bearing associated with the alert looked abnormal. Because the temperature was increasing while vibration was normal, MaintenanceOpt identified one of the most likely causes of the temperature spike as inadequate lubrication or cooling. Although the MaintenanceOpt alert initially went unnoticed because the problem occurred on a weekend with no maintenance personnel on site and the value stayed under the DCS alarm trigger value, the user was able to identify and fix the low oil problem within a few hours of seeing the alert and the temperature returned back to normal. The alert was closed and comments were recorded in the system for future reference. The plant was able to identify, diagnose and quickly resolve this issue using the historical mode in MaintenanceOpt.

3.4 Analysis of Mercury Speciation and Removal Process

The following section describes the analysis of mercury removal across post-combustion equipment on LMS U2. This analysis was performed to validate data gathered from the available Hg CEMS and to look for removal process effects in that data.

This analysis shows how the data was hand cleaned to select only samples of verifiably high quality, then compares the values at the ESP inlet, FGD Inlet and Stack. An analysis was also carried out to look for observable effects of FGD operation on removal rates.

As discussed below, it was found that the total amount of mercury removed across the ESP is essentially zero (to within measurement error). However, significant mercury oxidation occurs across the ESP. It was also shown that the FGD removes most of the oxidized mercury; thus, oxidation of mercury across the ESP is important to the total mercury removal rate of the FGD. It was also shown that there is a slight increase in elemental mercury across the FGD (commonly referred to as re-emission).

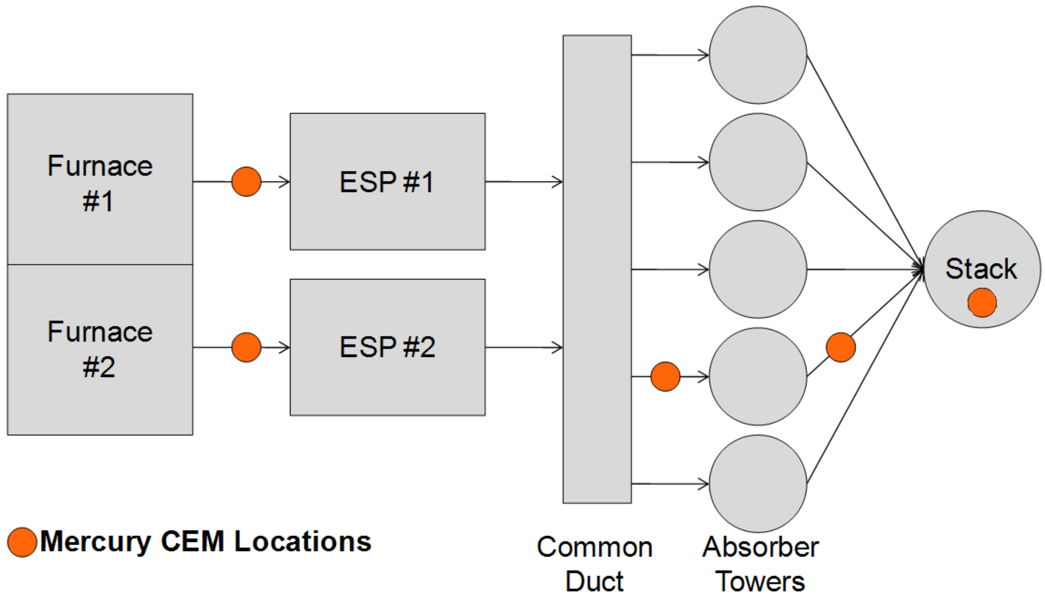

Figure 15: Mercury CEM Locations

Since the outlet FGD analyzer measures the same stream as the stack analyzer, the stack analyzer is used in this report. It is our belief that the stack analyzer is more accurate and reliable, demonstrated by much higher overall up-time and more consistent reporting over time (fewer obvious anomalies).

The amount of inlet FGD data was limited but was sufficient to support some significant conclusions. Figure 16 shows the amount of total mercury at the FGD inlet over a 150 day period. Areas in white are good data while areas in gray, yellow and red are excluded. Data from January 1 to May 30, 2009 was selected for analysis because stack measurements were available.

All mercury data was filtered to determine the quality of data. A quality status of good was assigned to a mercury measurement if it passed all quality filtering. If the measurement did not pass the quality filtering, it was assigned a quality status of bad and not used in the final analysis. The quality filtering was composed of three types: load, value and comparison filtering. These three types of filters are described below:

1. Load Filtering: Mercury data is given a bad status if the unit is off (at a load less than 300 MW), recently came out of an outage (within the past 4 hours), or the value of the load is unknown due to a bad status on the load sensor. If the mercury data is given a bad status due to load filtering, the region is shaded gray in Figure 16 and similar figures.
2. Value Filtering: If the mercury measurement has a bad value, is unknown due to a sensor or communication problem, or is out of range (less than 1 and greater than 40 in most cases), it is given a bad status. In this case, the region is shaded yellow in Figure 16.
3. Comparison Filtering: Because of quality issues associated with PSA analyzers, the values from these analyzers were compared to the stack measurements. If the ratio of the expected deviation between the stack and PSA measurements were greater than 25%, the measurements were given a bad status. (This prevented cases such as inlet ESP data measured in the PSA analyzer from being less than the data measured at the stack – such cases made no physical sense and thus the results were removed from the final analysis.) In this case, the region is shaded pink as shown in Figure 16.

Data that remains after the load, value and comparison filtering is deemed to be of good quality and is used in the analysis – this data is shown in white in Figure 16. Any data removed due to filtering is considered to be of bad quality.

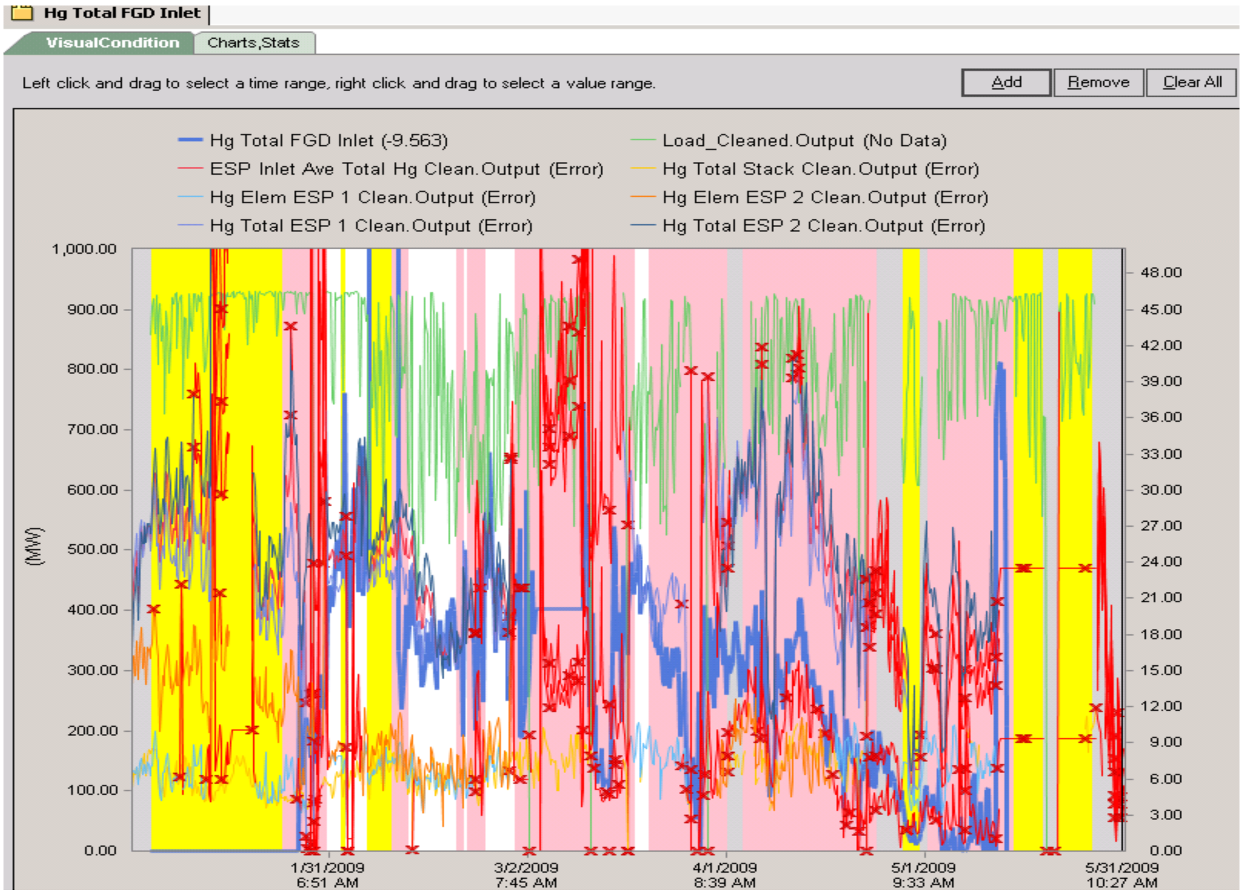

Figure 16: Total Mercury at the FGD Inlet (solid blue line) and other variables of interest, 1/1/09-5/31/09

Figure 17 shows a histogram, statistics and a chart of the good status data for total inlet FGD mercury over the time period of interest. From this figure, it can be seen that the average total inlet FGD mercury is 19.8 micrograms per normal square meter. The analyzer provides verifiably good status data 13% of the time over this period – this equates to approximately 18 days of valid data.

Figure 17: Total Good Status HG at FGD Inlet - 1/1/09-5/31/09

Figure 18 and Figure 19 show the same data as in Figure 16 and Figure 17 except on a different time scale (February 1 to March 31, 2009). The inlet total mercury to the ESP is shown in Figure 18. It is worth noting that the inlet total mercury to ESP and FGD are very similar.

Figure 18: Inlet Total FGD Hg (solid blue line) and other variables of interest, 2/1/09-3/1/09

Figure 19: Total Good Status HG at FGD Inlet - 2/1/09-3/1/09. The area in white shows data of valid status.

Figure 20 shows similar plots for elemental mercury at the inlet of the FGD. Since most of the valid data occurs from February 1 to March 1, 2009, only this data is shown for elemental mercury.

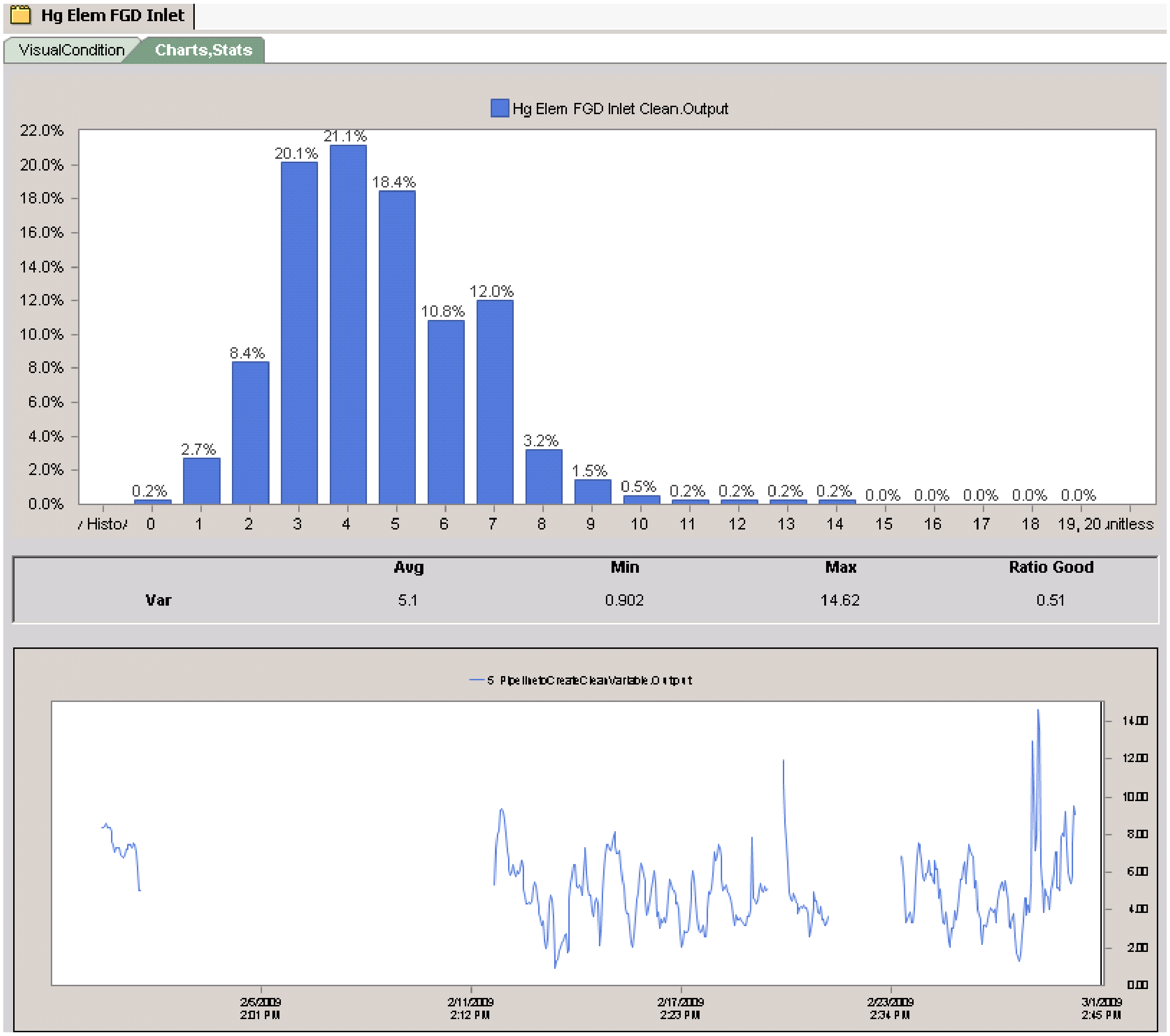

Figure 20: Histogram, Statistics & Chart of Valid Elemental Hg at FGD Inlet 2/1/09-3/1/09.

3.4.1 Comparison of Mercury at ESP inlet, FGD inlet and the Stack

Using the data described in the previous section, the following section compares the amount of mercury at the inlet of the ESP, inlet of the FGD and stack over the time period of valid inlet FGD data. (The data for the inlet of the ESP and the stack were also valid over the same time period; thus, we were able to do a direct comparison of these values, where status was good, between January 1 - May 31, 2009.)

Table 8 shows the average values for the mercury analyzer measurements over the time period of comparison. Table 9 shows the percentage of elemental mercury to total mercury at the inlet to the ESP, inlet to the FGD and at the stack.

Mercury	**Average [μg/m^3]**
Total at Inlet to ESP	19.8
Elemental at Inlet to ESP	6.9
Total at Inlet to FGD	19.5
Elemental at Inlet to FGD	5.0
Total at Stack	6.5
Elemental at Stack	5.8

Table 8: Average Hg at the Inlet to the ESP, Inlet to the FGD & Stack

Location	**Percentage of Elemental to Total Mercury**
Inlet to ESP	35%
Inlet to FGD	25%
Stack	89%

Table 9: Percentage of Elemental Hg to Total Hg at Various Locations

A number of important conclusions can be drawn from the results shown in these two tables:

1. **No Mercury Removal in ESP:** Over the period of comparison, no significant difference in total mercury is measured between the inlet of the ESP and inlet of the FGD. Thus, we conclude that no significant amount of measured mercury is removed in the ESP.
2. **Oxidation of Mercury in the ESP:** The amount of elemental mercury decreases from an average of 6.9 to 5.0 across the ESP; thus, we conclude that a portion of the elemental mercury is being oxidized in the ESP. Table 9 provides further evidence of oxidation across the ESP – the ratio of elemental to total mercury significantly decreases across the ESP.
3. **Slight Re-emission of Elemental Mercury in FGD:** A small amount of oxidized mercury capture in the absorber slurry is re-emitted as elemental mercury based upon the results shown in Table 8. Elemental mercury increases from 5.0 to 5.8 across the FGD.
4. **Significant Mercury Capture in FGD:** As shown in Table 8 and Table 9, the FGD removes a significant portion of the oxidized mercury. Elemental mercury accounts for 89% of the emitted mercury. Thus, increasing the amount of oxidized mercury is very important for mercury removal.

Figure 21 shows the total mercury at three locations (inlet to ESP, inlet to FGD, and stack) along with load for the month of February. It can be observed that the total mercury at the inlet to the ESP and FGD are approximately the same. The total outlet mercury at the stack is significantly less than that at the inlet to the ESP.

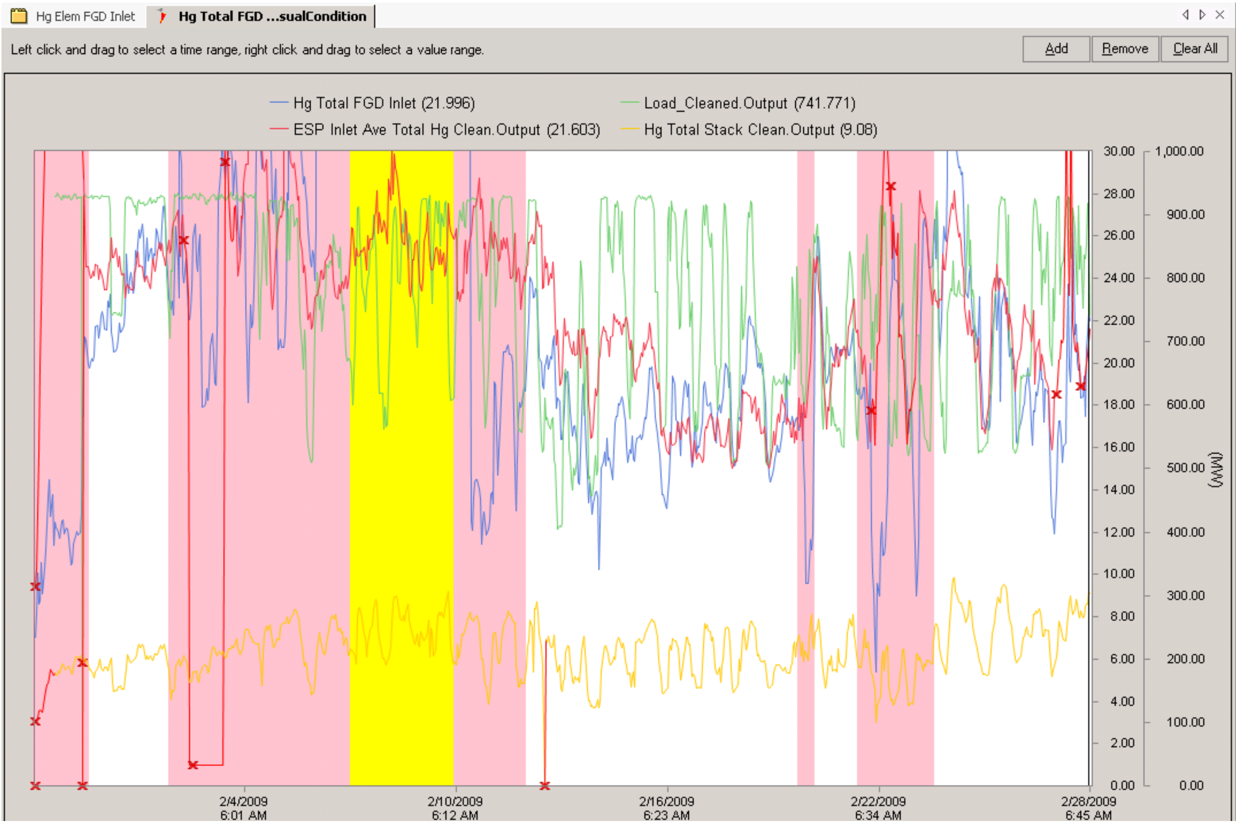

Figure 21: Total Hg at 3 locations along with load for month of February.
Note that the areas of valid data are in white

Figure 22 shows the elemental mercury at three locations (inlet to ESP, inlet to FGD, and stack) along with load for a typical day in February. (One day was selected so that the slight difference in trends can be observed.) In this case, the elemental mercury at the inlet to the ESP is highest while it is lowest at the inlet to the FGD.

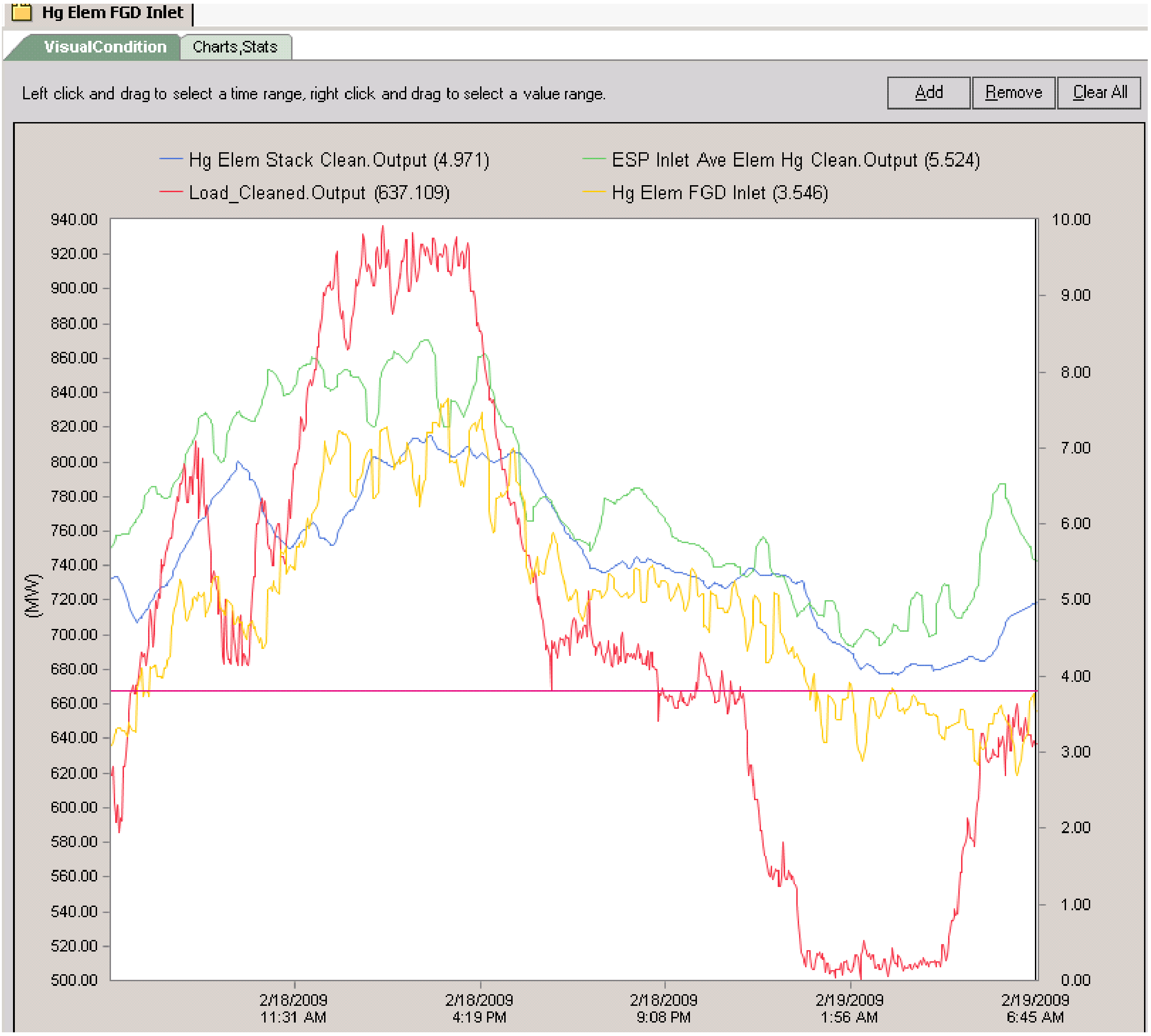

Figure 22: Elemental Hg at 3 locations along with load for typical day in February 2009

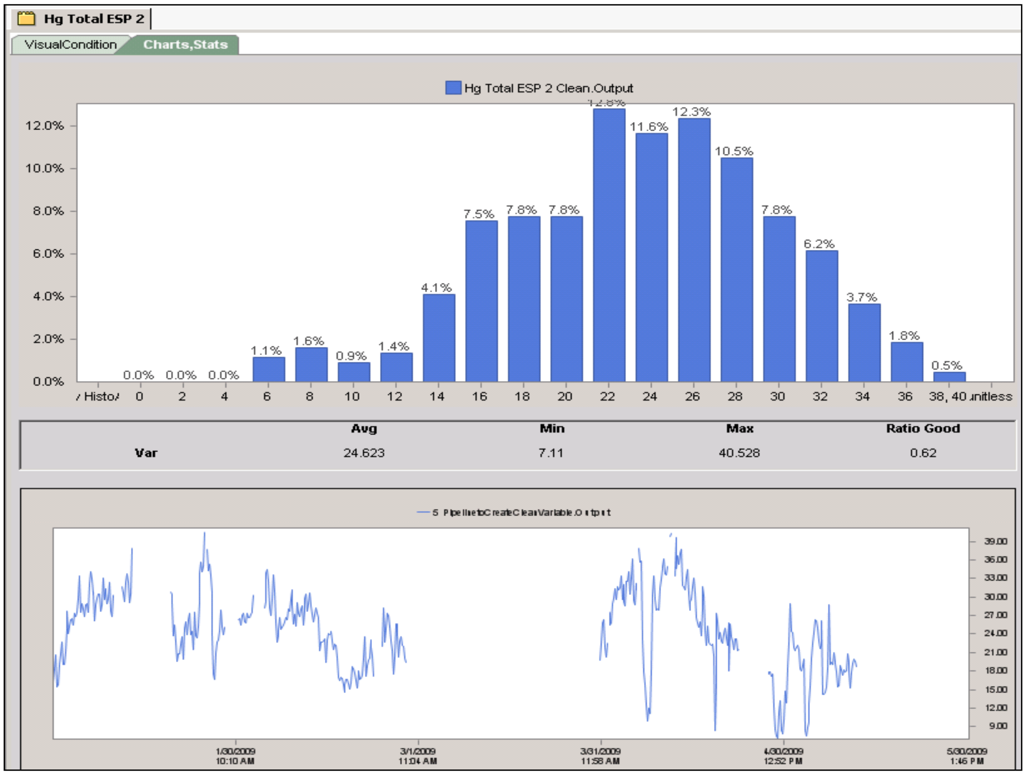

Figure 23: Hg Total ESP 2

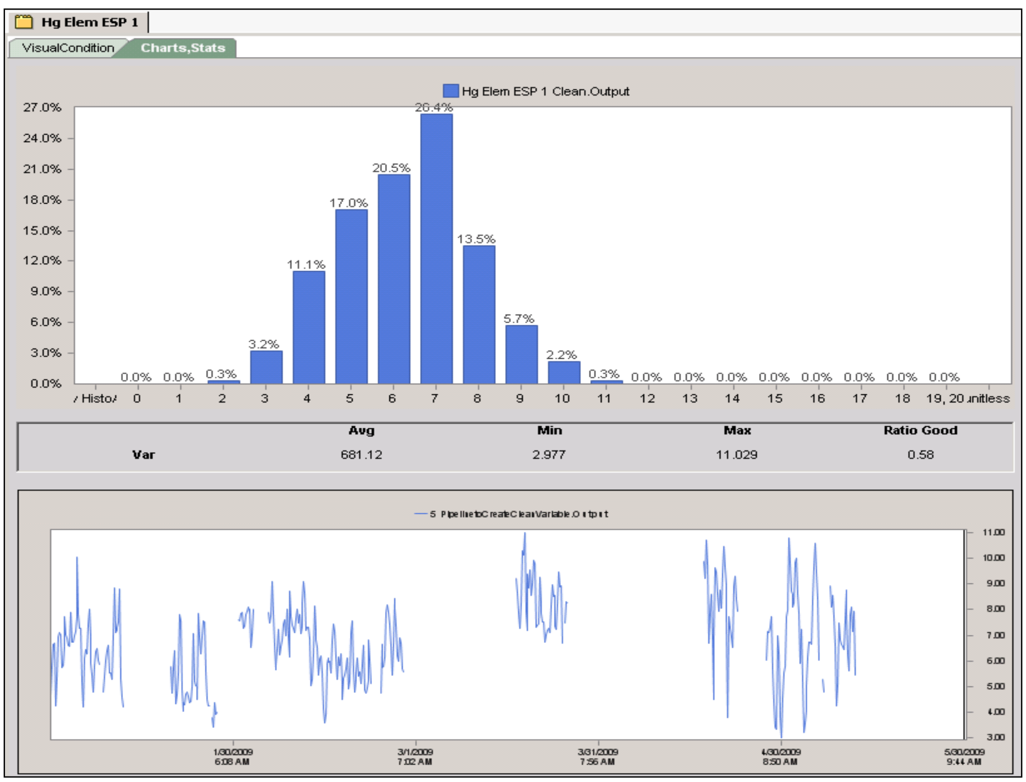

Figure 24: Hg Elemental ESP 1

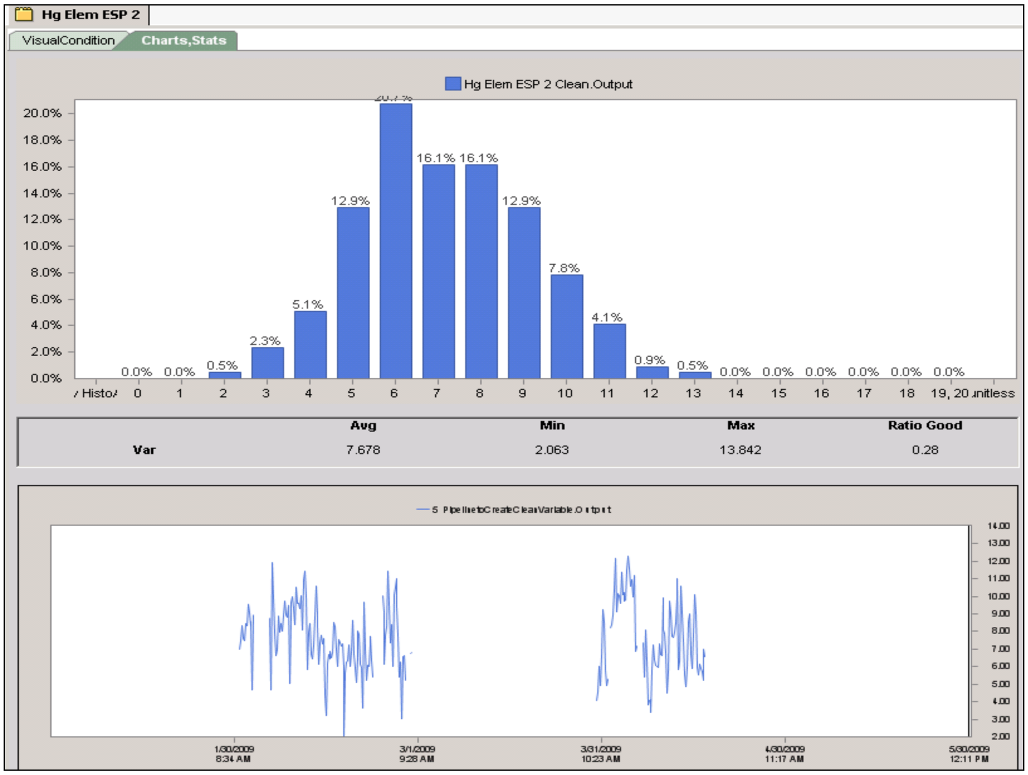

Figure 25: Hg Elemental ESP 2

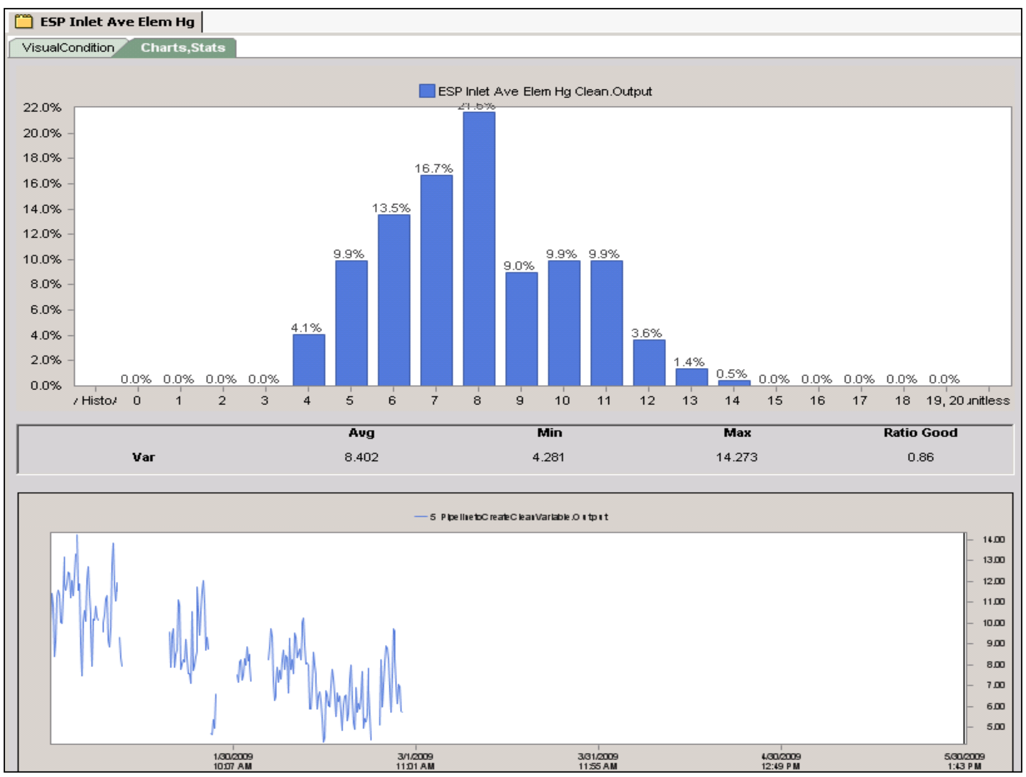

Figure 26: ESP Inlet Average Elemental Hg

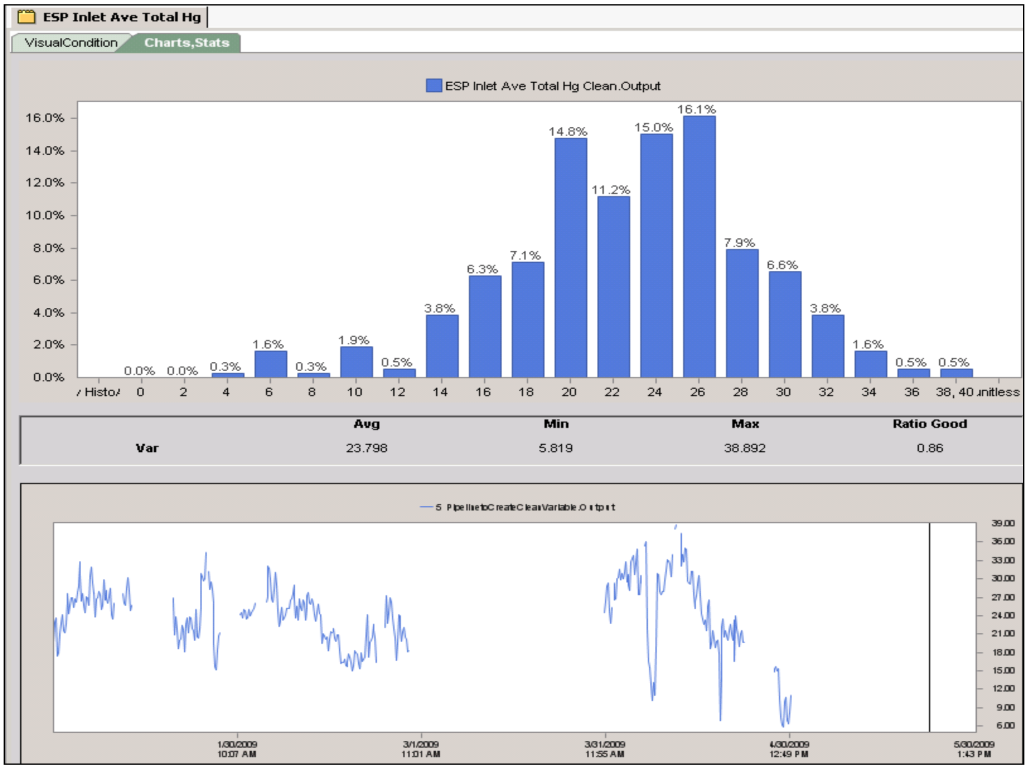

Figure 27: ESP Inlet Average Total Hg

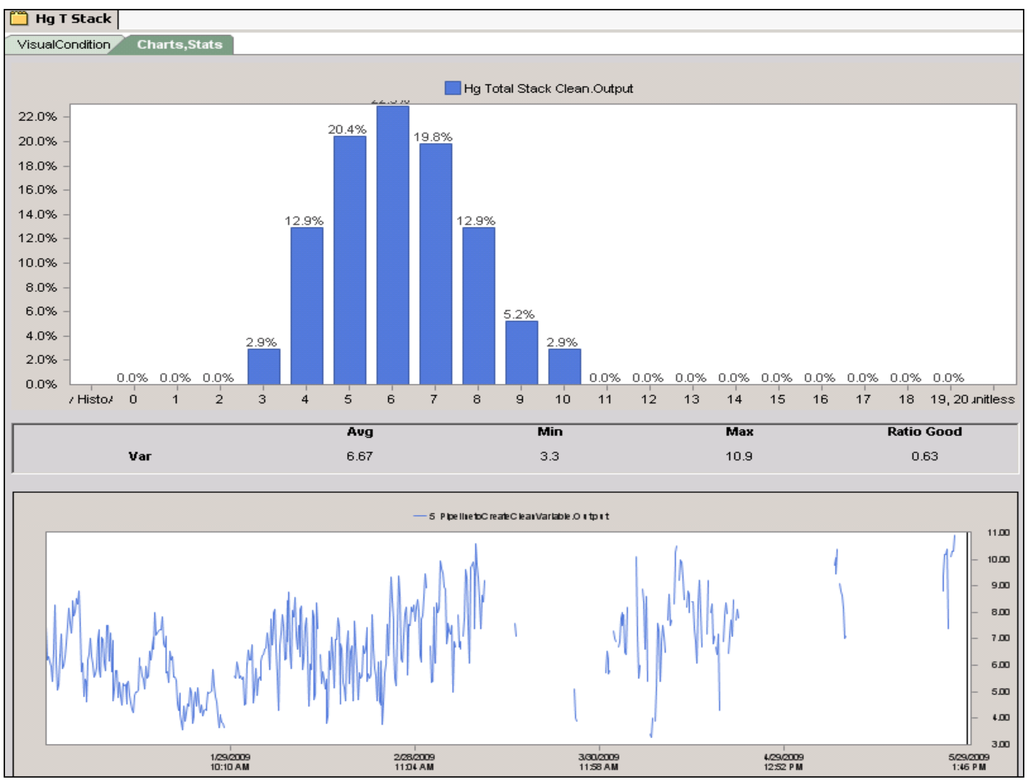

Figure 28: Stack Total Hg

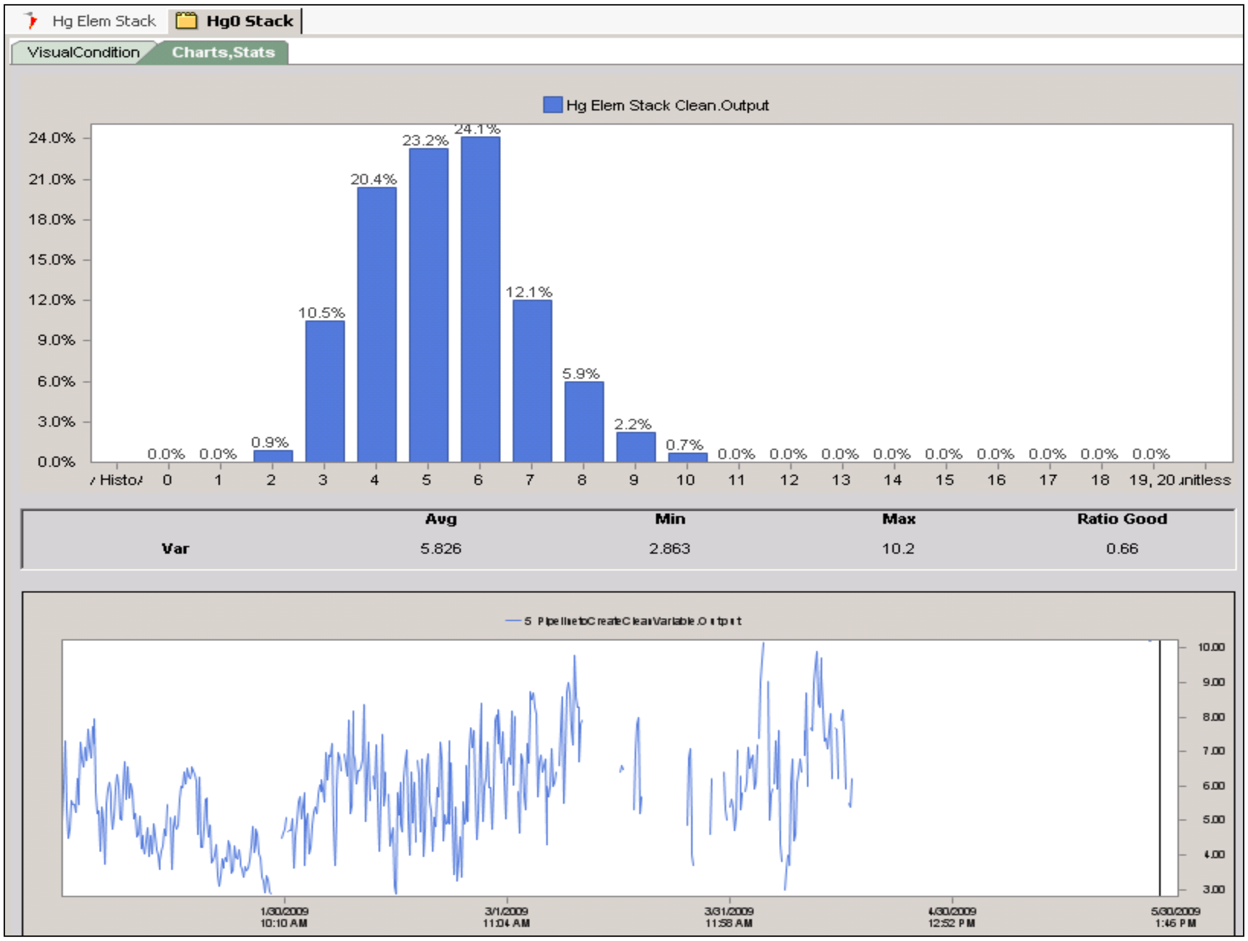

Figure 29: Stack Elemental Hg

3.4.2 Mercury Removal Estimate

Mercury Removal was defined as follows using the data shown in the previous section.

$$\%\ \text{Mercury Removal} = \frac{(\text{FGD Outlet Total Hg} - \text{ESP Inlet Total Hg}) * 100}{\text{ESP Inlet Total Hg}}$$

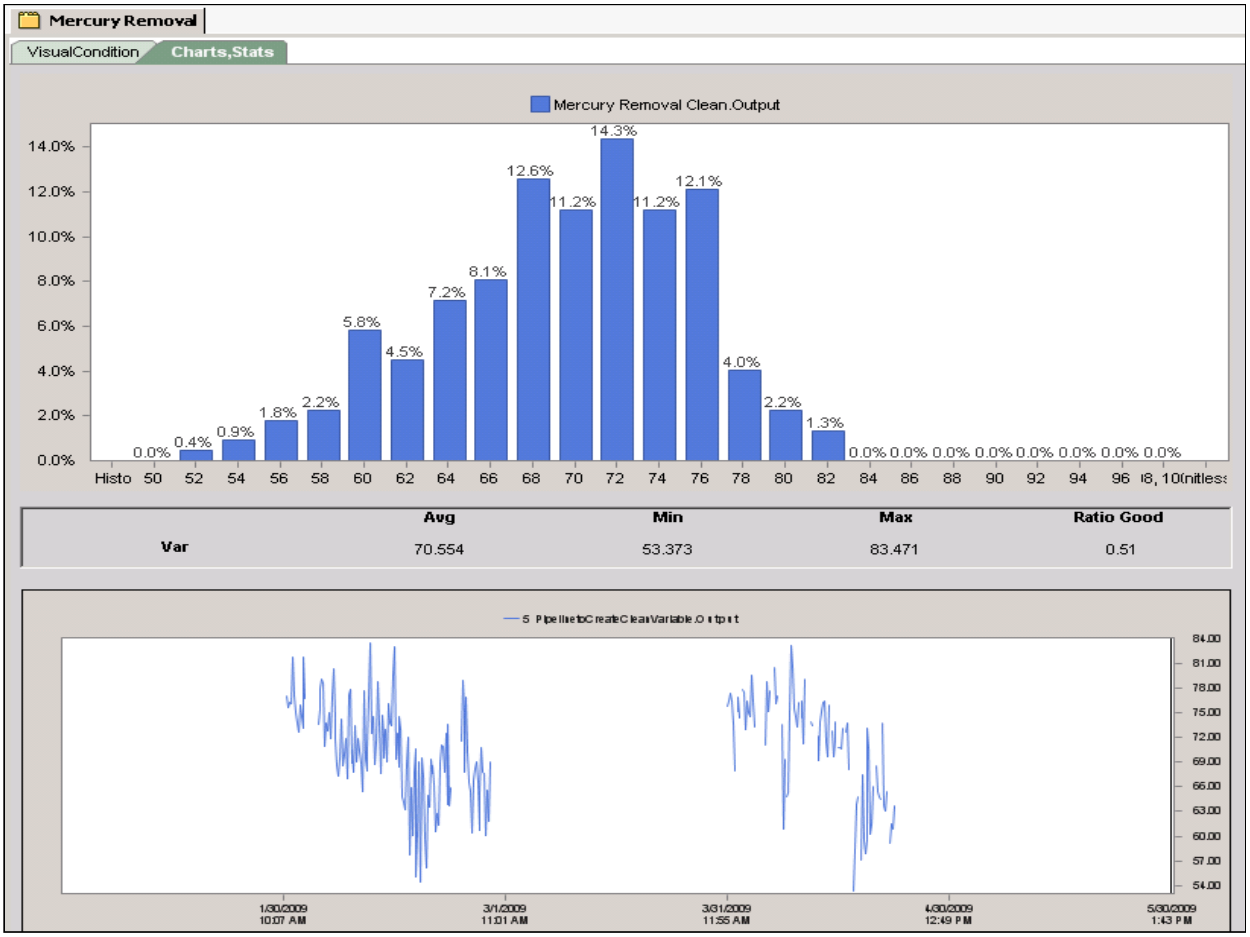

Figure 30: Hg Removal

3.4.3 Effects of FGD Operation on Mercury Removal

The primary function of the FGD is to remove SO_2 from the flue gas stream. As currently designed, the FGD system at LMS U2 has the capability of removing 90-95% of the SO_2 from the flue gas.

The FGD removes SO_2 by spraying LMS U2 slurry through the flue gas in an absorber tower. The removal rate is affected by the pH of the slurry along with the number of pumps in service.

The total amount of SO_2 removed at LMS U2 is also determined by the amount of flue gas that goes through the absorbers. A bypass damper can be used to route flue gas around the scrubbers.

As noted in the previous section, the FGD also removes a large percentage of the oxidized mercury from the flue gas. Since changes in the number of pumps, bypass and pH all affect SO_2

removal, an investigation was done into whether changes in these values also affect mercury removal.

To perform this investigation, data were analyzed where inlet FGD and stack mercury analyzer data were available over the period from January 1 to May 31, 2009. Figure 31 shows the pH data over the period of interest. The area shown in white is data where the inlet FGD analyzer had good status.

Figure 32 shows a histogram, statistics and chart for the data of interest. As can be observed in Figure 32, there is very little variation in the data over this time period; thus, it was concluded that there is insufficient data to determine mercury removal as a function of pH from inlet FGD to stack.

Figure 33 shows the bypass damper position from January 1 to May 31, 2009. For all practical purposes, the bypass damper shows no variation – it is always closed.

Figure 34 shows the pump amps for the four pumps used on absorber D from January 1 to May 31, 2009. As can be seen from this figure, two pumps were in service at all times during this time period.

The requirements of FGD operation are a function of gypsum and SO2 credit markets relative to auxiliary costs. Operation of the FGD as shown in the following figures is typical of operation of most FGDs. The pH, number of pumps and bypass are typically not moved. The lack of change in gross FGD operation allows an investigation to be made into the effect changes in the combustion area have on removal rates, free of disturbances.

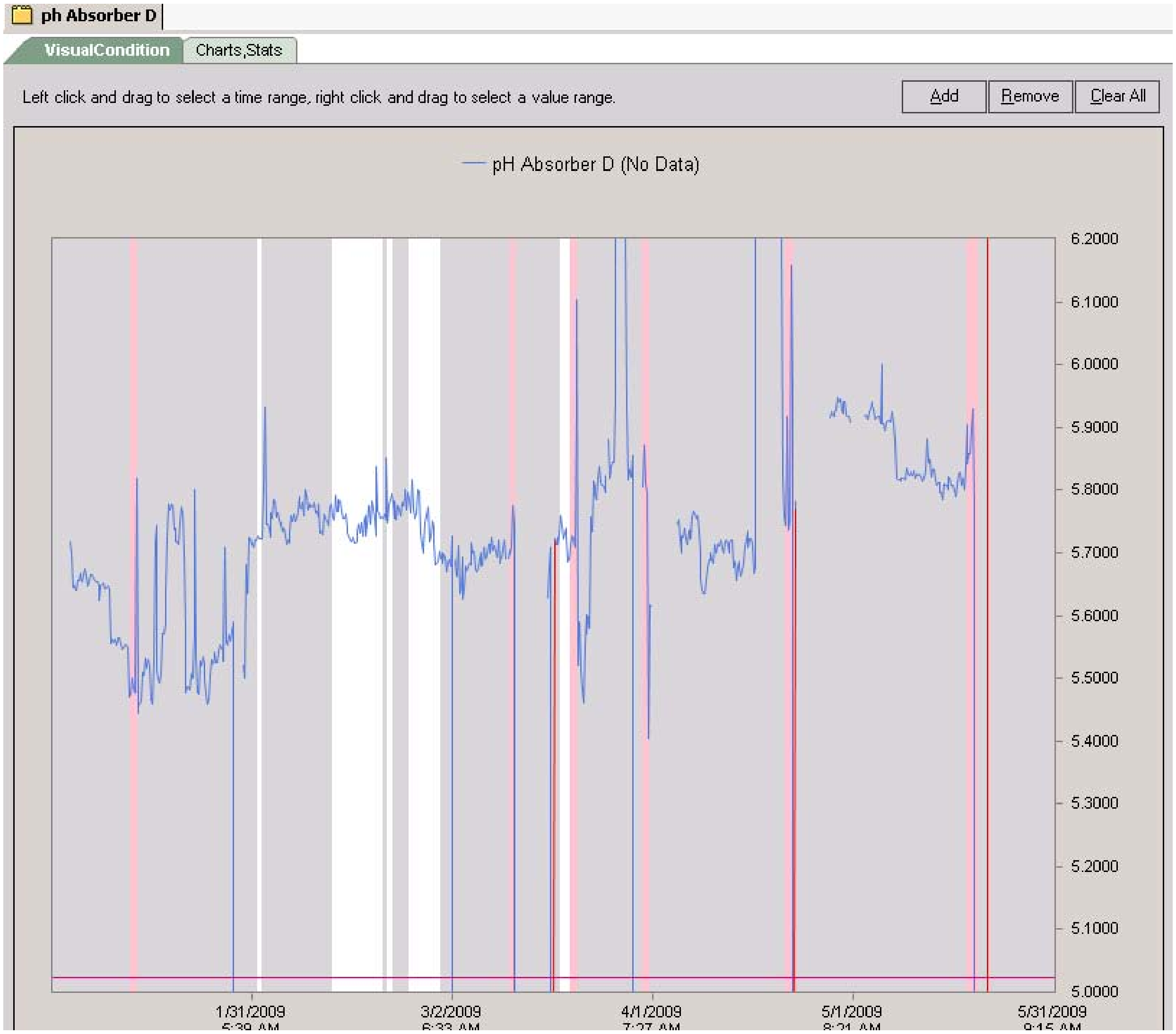

Figure 31: pH in Absorber Tower D, January 1-May 31, 2009.
The area shown in white indicates areas where FGD inlet analyzer data are available.

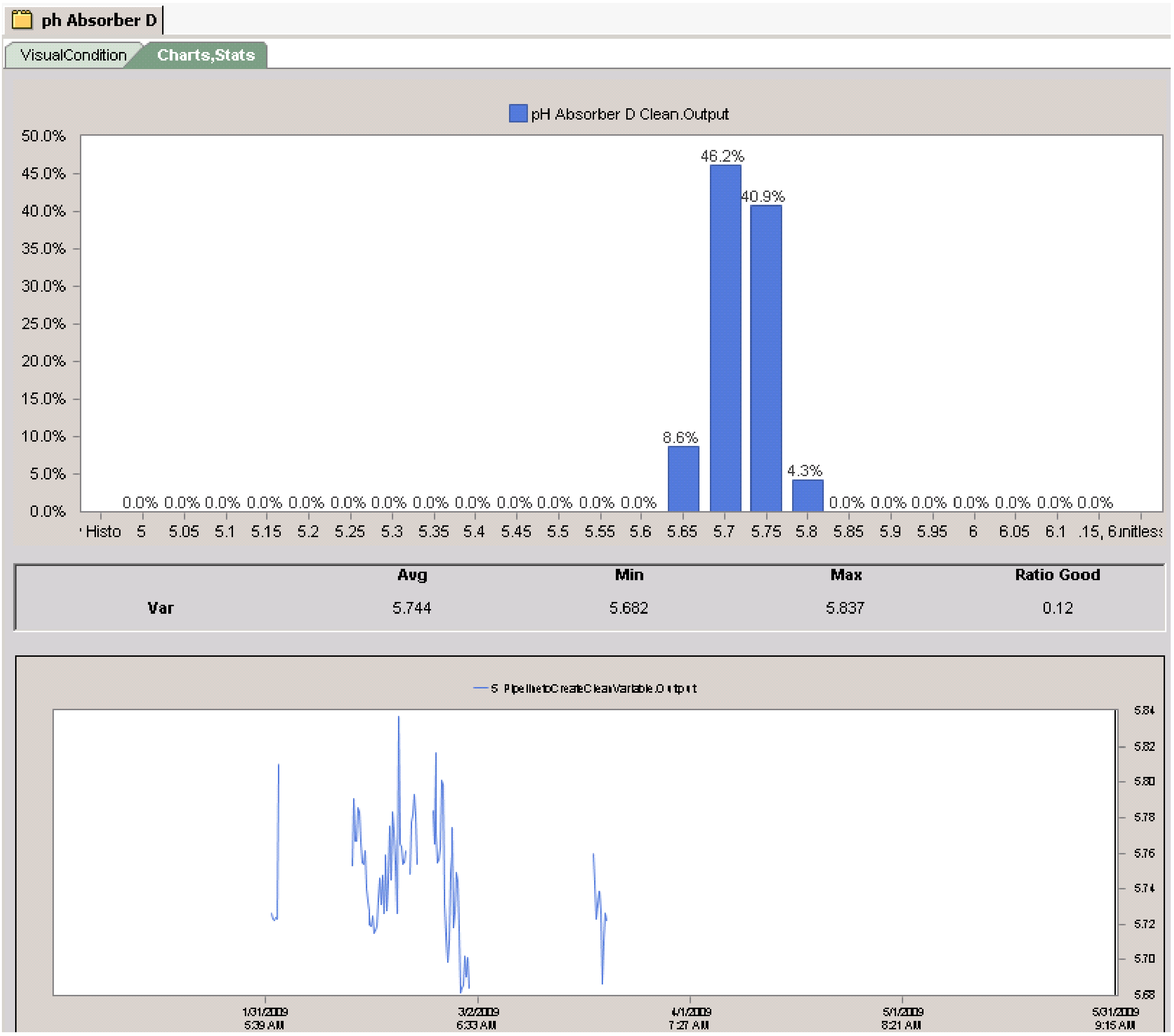

Figure 32: Histogram, Statistics and Chart of pH in Absorber Tower D
The analysis period is January 1 to May 31, 2009. The data show little significant variation from the average value of 5.74.

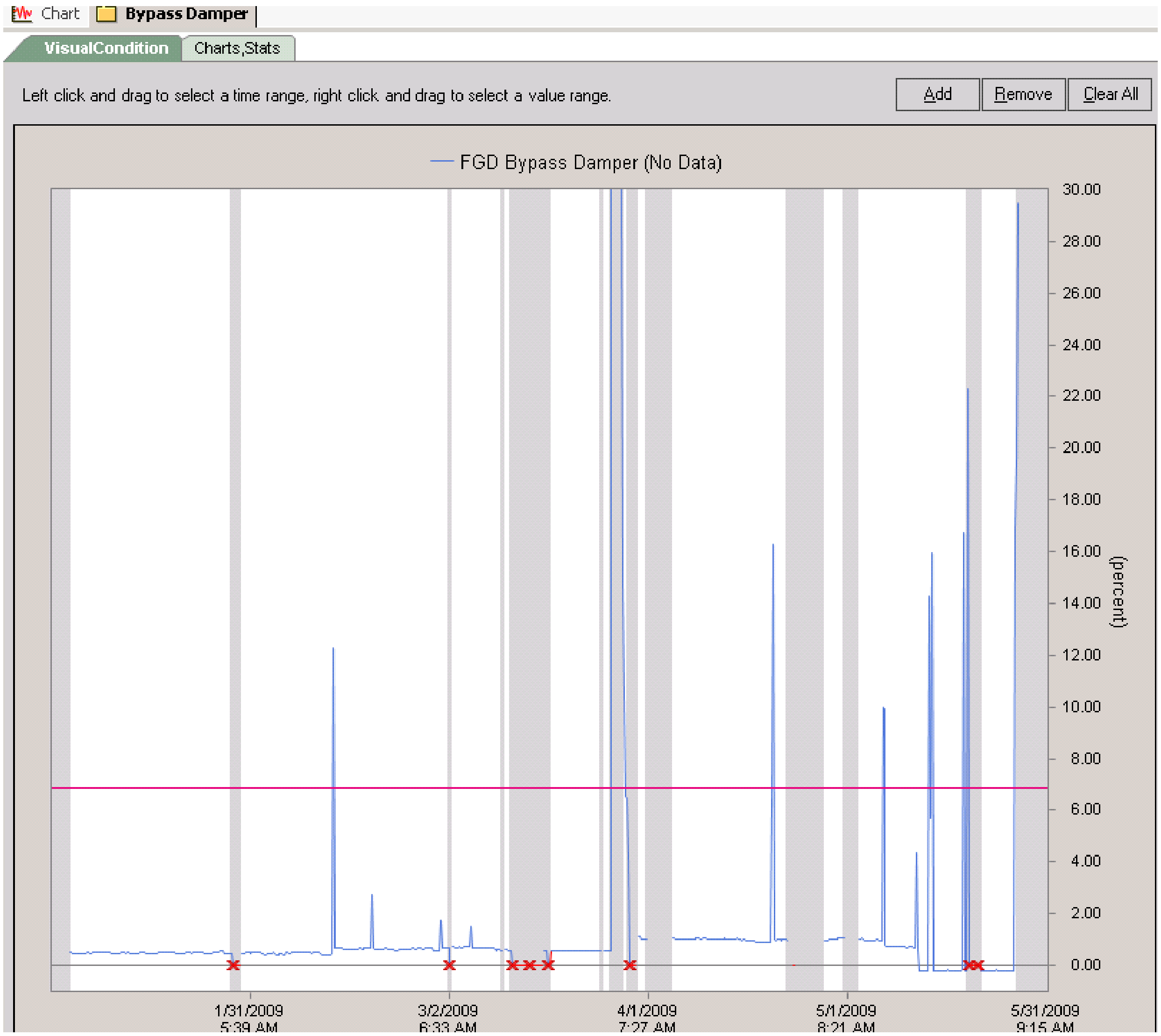

Figure 33: Bypass Damper Position January 1-May 31, 2009
The bypass damper was closed for all practical purposes during this time period.

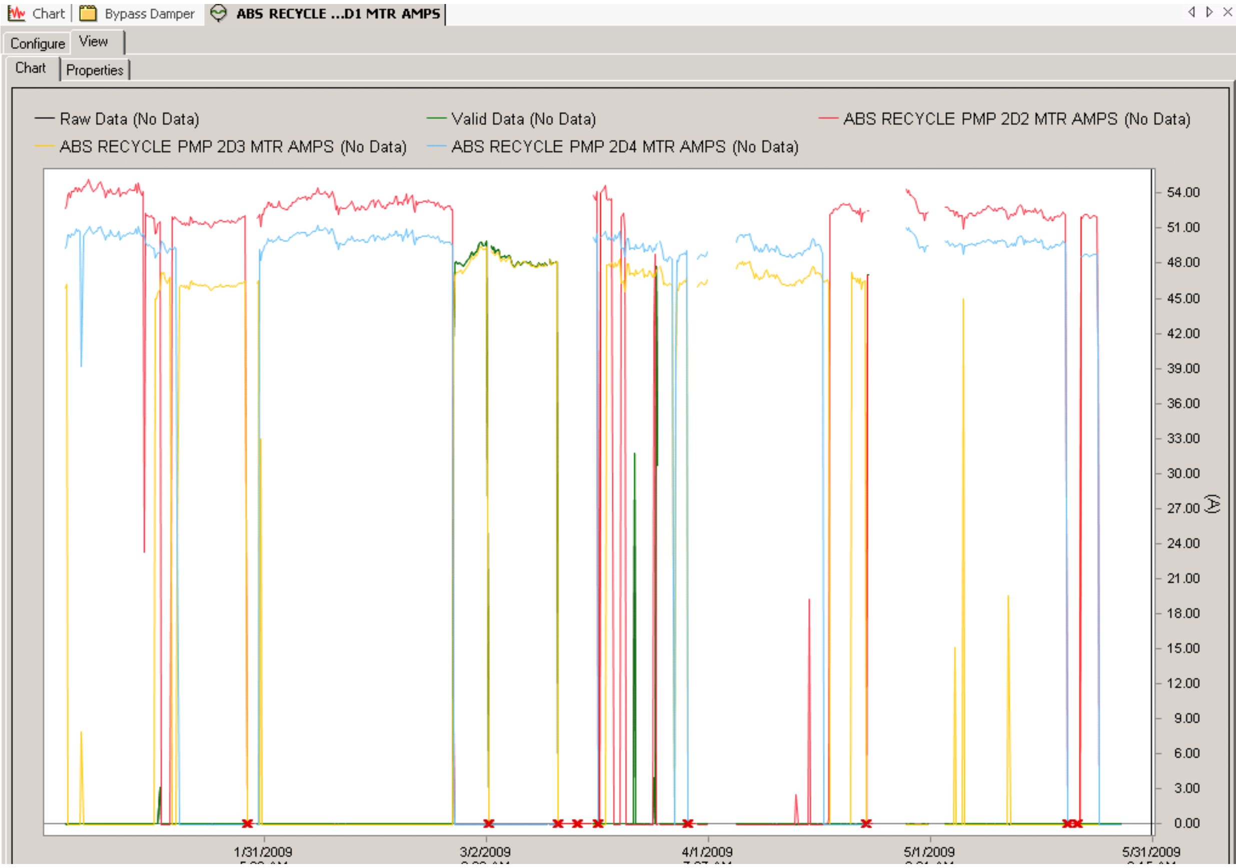

Figure 34: Pump amps for Absorber Tower D January1-May 31, 2009
In the case shown in Figure 34, two pumps were in service at all times, thus, there is no variation in the number of pumps.

3.4.4 Mercury Removal Process Conclusions

The analysis carried out showed that the total amount of mercury removal across the ESP is essentially zero (to within measurement error). The amount of mercury at the inlet of the FGD and ESP were found to be approximately equal. It was shown that significant mercury oxidation occurs across the ESP. The ratio of elemental mercury to total mercury decreased from 35% to 25% across the ESP.

It was also shown that the FGD removes most of the oxidized mercury. The amount of oxidized mercury in the FGD outlet was only 11%. It was also shown that there was a slight increase in elemental mercury across the FGD (commonly referred to as re-emission).

The results also support the importance of upstream changes to combustion on the total mercury reduction from the inlet of the ESP to stack, suggesting that primarily combustion processes have a large effect on removal rates.

3.5 Mercury Removal and Stack Mercury VOA Development

A virtual on-line analyzer (VOA) is a regression based model, trained on measured data to match a target measured value as a function of other observed values. The model can be used to estimate what the target measurement would have been in situations where a measurement was not taken, based on the values of the other variables. This approach was used in the broader data analysis to compensate for the low availability of mercury CEMS data. This section describes how the mercury VOA's used in the analysis to follow was developed.

Neural network technology was used to develop the virtual on-line analyzer model. Neural networks are a form of nonlinear regression (curve fitting) that is well suited for developing models in relatively data poor environments such as encountered in this project. The neural network models are developed by adjusting the free parameters of the model to match a set of actual data. This was accomplished using the backpropagation algorithm. The performance of the model is monitored using a second hold out data set which was used to guarantee optimal selection of the free parameters of the model.

Once developed, the Mercury Removal and Mercury Stack Total models were used to estimate their respective values as functions only of the inputs they use. The models trained were of sufficient quality to be useful in estimating the behavior of Mercury over medium to long time frames, which is how they were used in the benefits analysis.

3.5.1 Mercury Removal VOA

The Mercury removal VOA model was defined as:

Hg Removal % = NN(O2, tilts, load)

NN() represents the neural models and O2, tilts and load are inputs to the model. Thus, in this case, given the O2, tilts, and load, the neural network models were used to generate an estimate of mercury removal from the unit. Mercury removal was defined as the amount of mercury removed between the inlet of the ESP and the outlet at the stack.

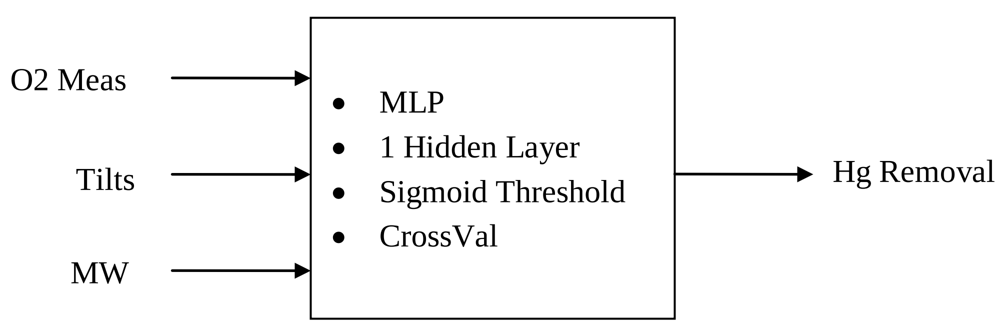

Figure 35: Hg Removal (VOA) Inputs

The data used for training the model were based upon the data available in January 1, 2009 to May 31, 2009 as described in the previous section. This data were divided into a training set and a test set. The data were then used to train the neural network model.

Figure 36 shows the neural model prediction of Mercury Removal for the entire demonstration period (1/20/09 – 6/25/10), where unit load was above 880MW, along with the data used to train the model. This plot shows how existing measurements can be used to develop a model that can then be used to extrapolate into regions where actual measurements are not available.

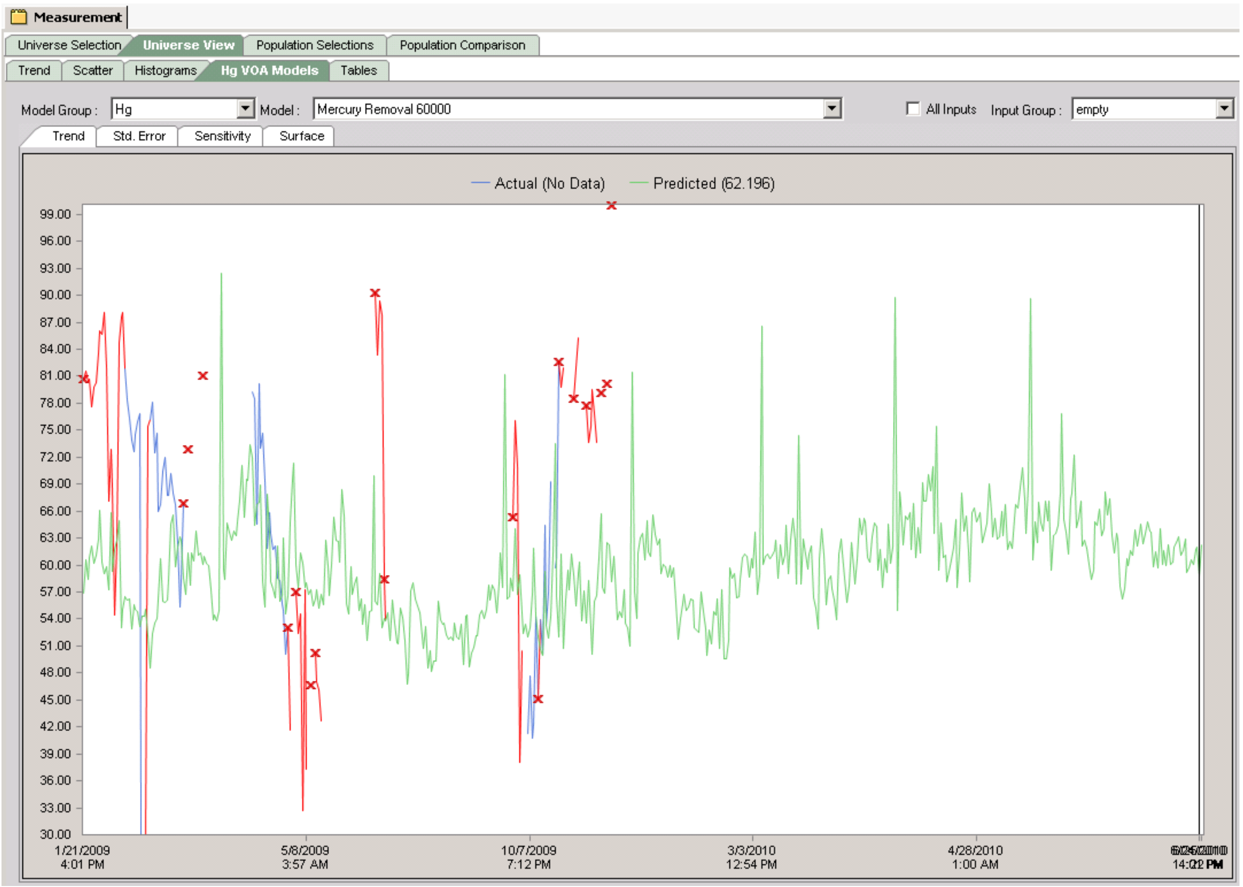

Figure 36: Model Predicted vs. Actual Hg Removal for 520 days (MW>880)
Blue data represent actual measurements that were cleaned and validated and available to train the VOA. Red data represent data that were collected but evaluated as bad. Green is the VOA prediction of what actual would have been (y-axis is % removal).

Figure 37 shows a scatter plot of the same signals vs. Unit Load (for all data not just when MW>880). It can be observed that the model captures the mean behavior of the measurement.

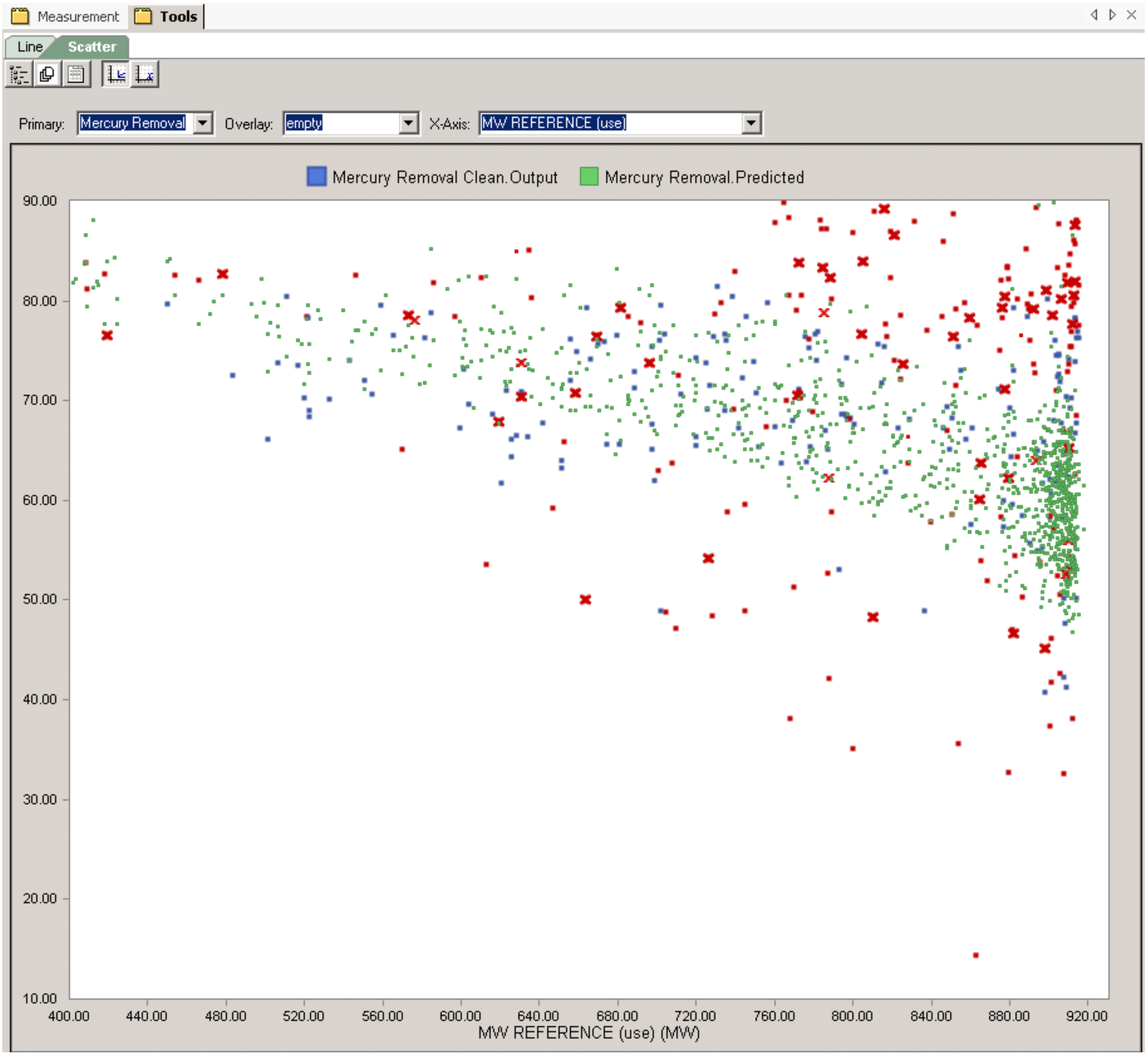

Figure 37: Model Predicted vs. Actual Hg Removal vs. Load for 520 days

In Figure 37, blue data represent actual measurements that were cleaned and validated and available to train the VOA. Red data represent data that were collected but evaluated as bad. Green is the VOA prediction of what actual would have been (y-axis is % removal).

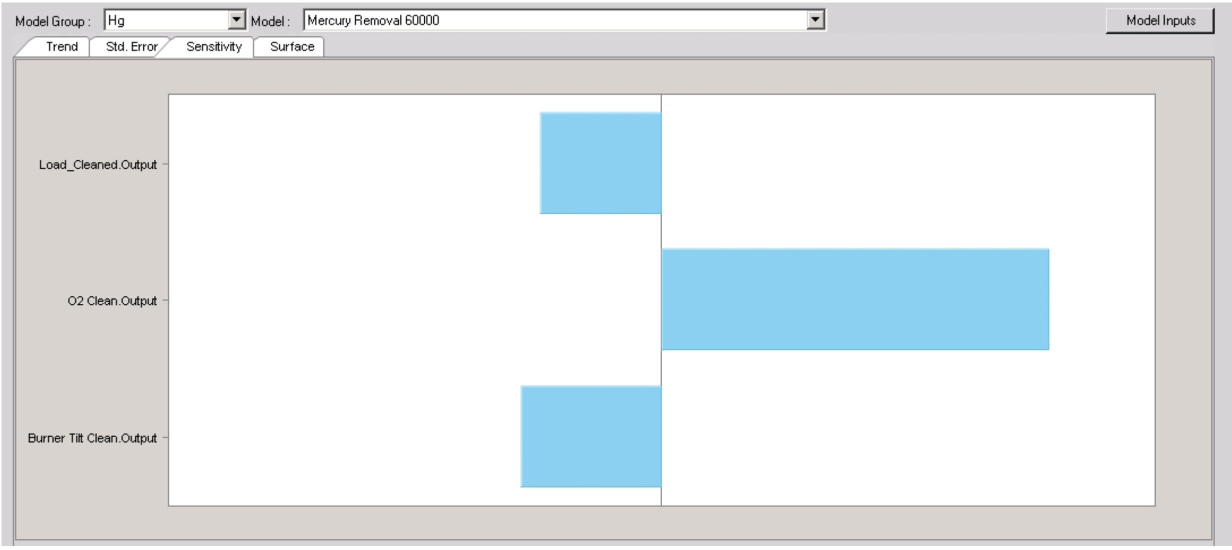

Figure 38: Sensitivity Analysis of Hg Removal Model

Figure 38 shows a sensitivity analysis (partial derivatives) of model predicted Hg removal with respect to each of its inputs. Sensitivity to the right of the center-line means a 1 to 1 directional relationship. In other words, an increase in the value of the input can be expected to result in an increase in the modeled output. Sensitivity to the left of the center line means the directional relationship is 1 to -1 or inverse. This means an increase in the input can be expected to cause the opposite response in the output.

Note there is no fuel blend input in the input space of this model, meaning this model is blind to the effects of fuel blend. This was due to the unavailability of good fuel blend data during the times when removal data were available, making a regression of their simultaneous behavior impossible. Although this is unfortunate, the contrast this model shows when compared to the Mercury Stack Total model, which does contain an input for fuel (significantly more Stack Hg CEMS data was gathered), supports the conclusion that fuel blending was a major (if not the major factor in improved Hg emissions).

Figure 39 through Figure 41 show the model predicted response of Mercury removal as a function of the model's inputs.

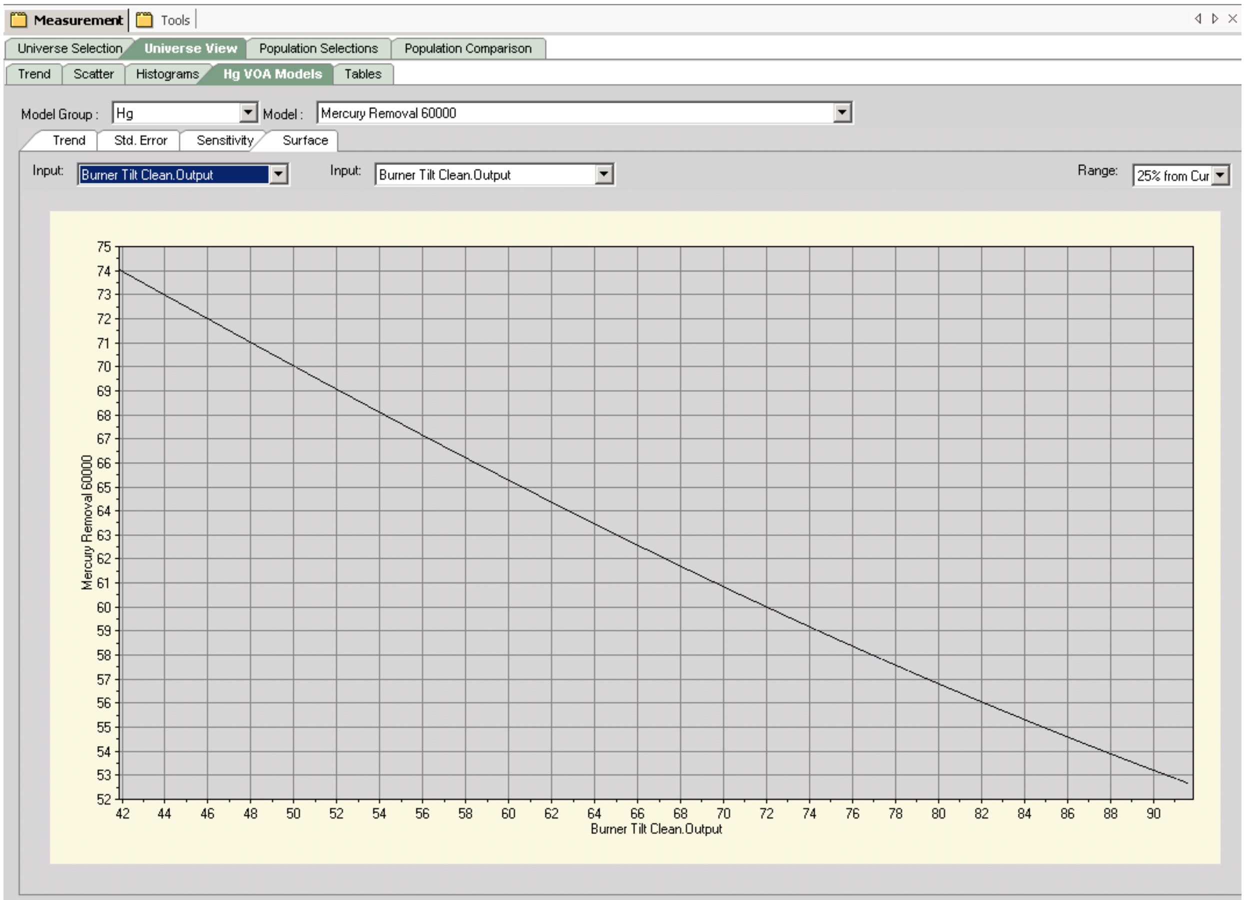

Figure 39: Response Surface Hg Removal Model vs. Burner Tilts

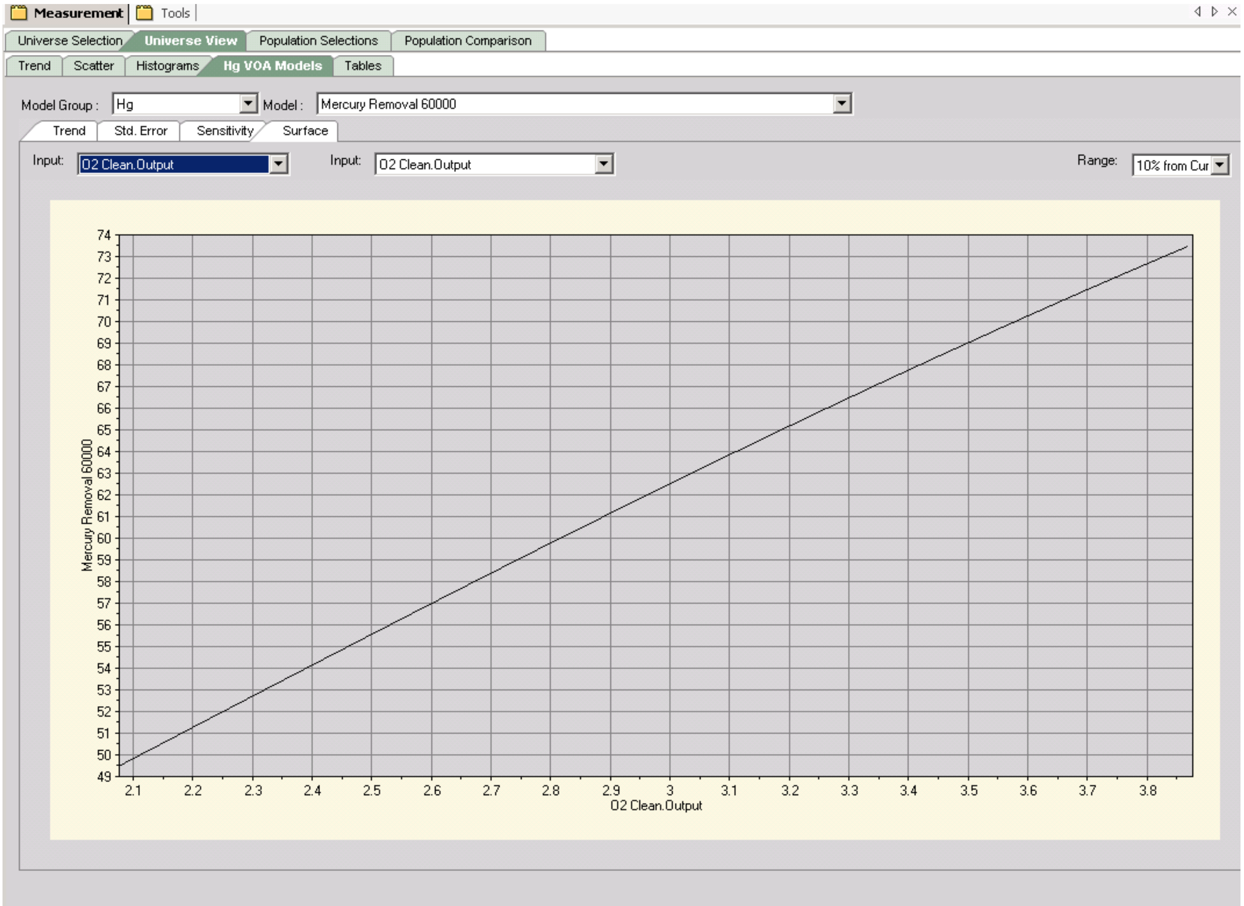

Figure 40: Response Surface Hg Removal vs. O2

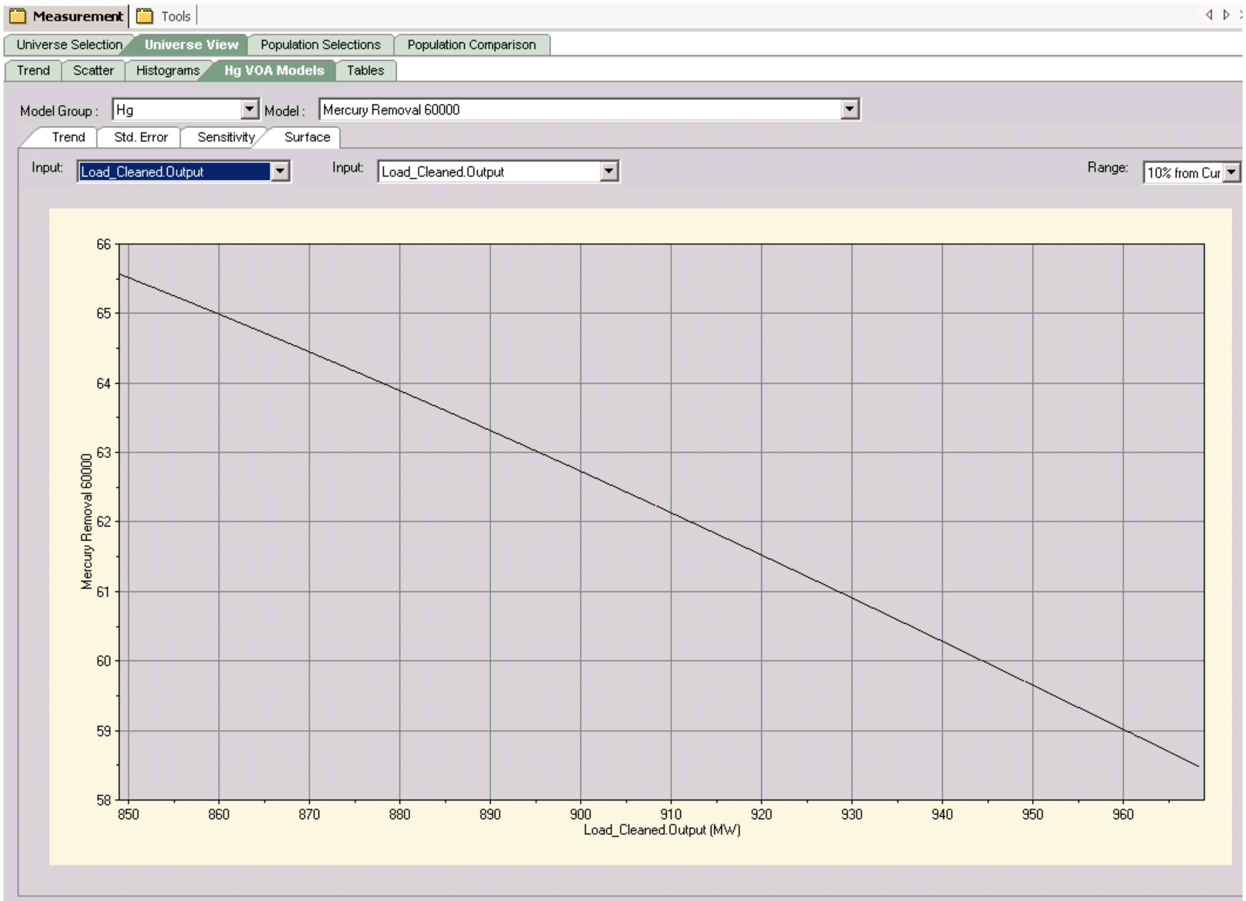

Figure 41: Response Surface Hg Removal vs. Load

3.5.2 Stack Mercury VOA

The total stack mercury emission VOA model was defined as:

Stack Total Hg = NN(O2, tilts, fuel blend, load)

NN() represents the neural models and O2, tilts, fuel blend and load are inputs to the model. In this case, given the O2, tilts, fuel blend, and load, the neural network models were used to generate an estimate of stack total mercury from the unit.

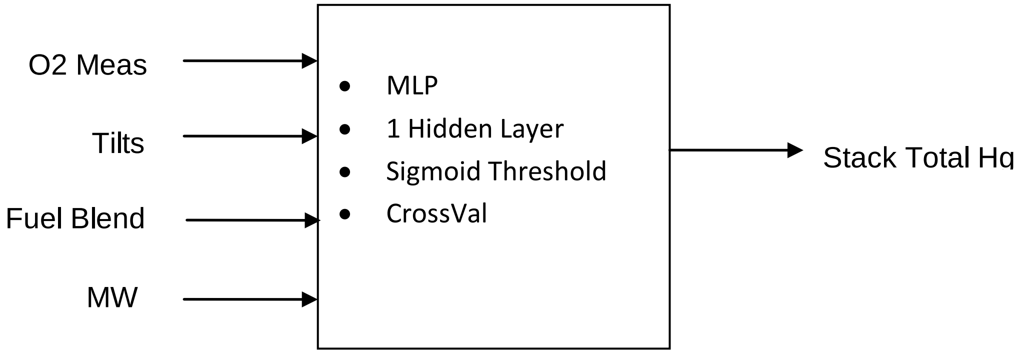

Figure 42: Hg Stack Total Model (VOA) Inputs

Approximately one year of data was used to train the model (January 2009 - December 2009). Fuel blend was available for a majority of this period, thus it could be included as an input in the model for total stack mercury.

Figure 43 shows the neural model prediction of Mercury Stack Total for the entire demonstration period (1/20/09 – 6/25/10), where unit load was above 880MW along with the data used to train the model. This plot shows how existing measurements can be used to develop a model that that can then be used to extrapolate into regions where actual measurements are not available.

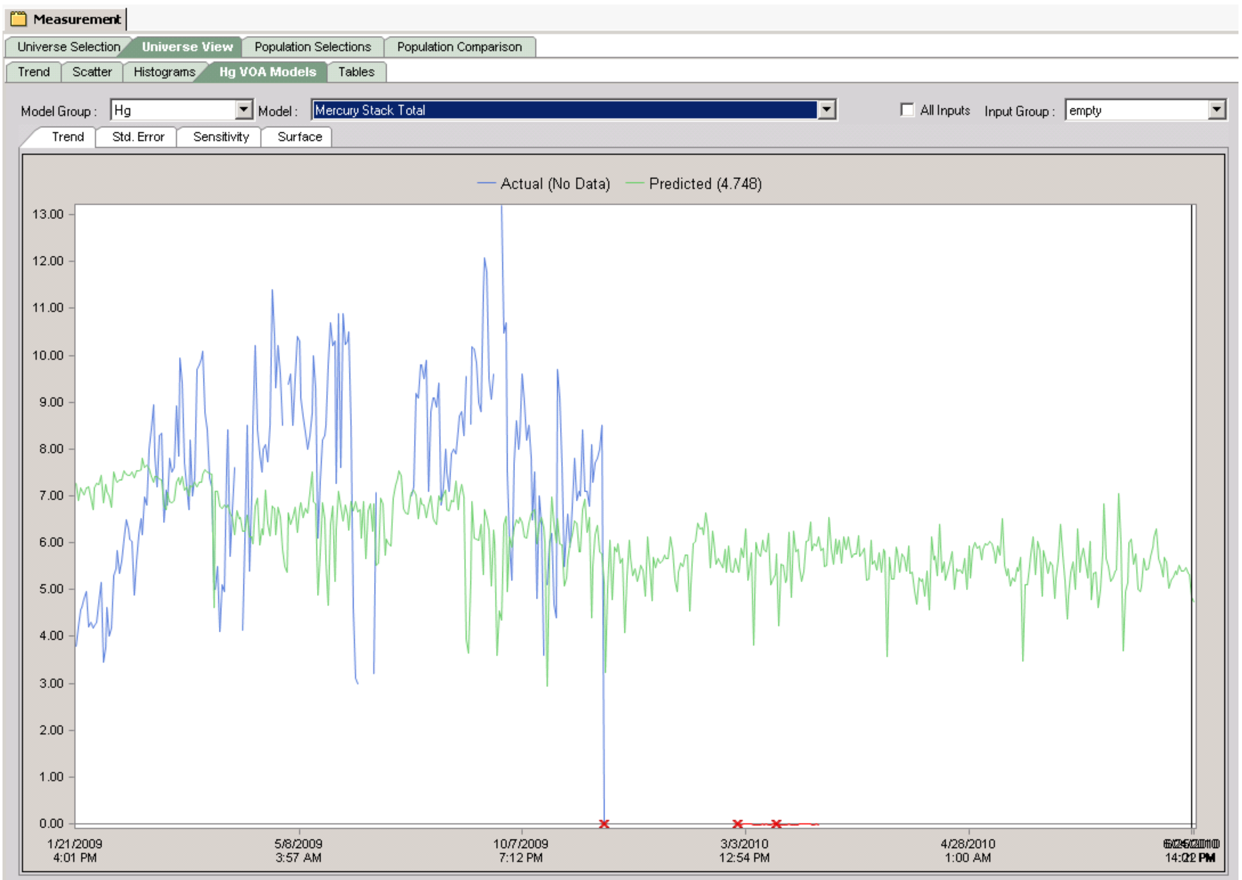

Figure 43: Model Predicted & Actual Hg Stack Total for 520 Days (MW>880)

In Figure 43, blue data represent actual measurements that were cleaned and validated and available to train the VOA. Red data represent data that were collected but evaluated as bad. Green is the VOA prediction of what actual would have been (y-axis is µg/m^3)

Figure 44 shows a scatter plot of the same signals vs. Unit Load (for all data not just when MW>880). It can be observed that the model captures the mean behavior of the measurement. It can also be seen that significantly more Stack Hg CEMS data were available.

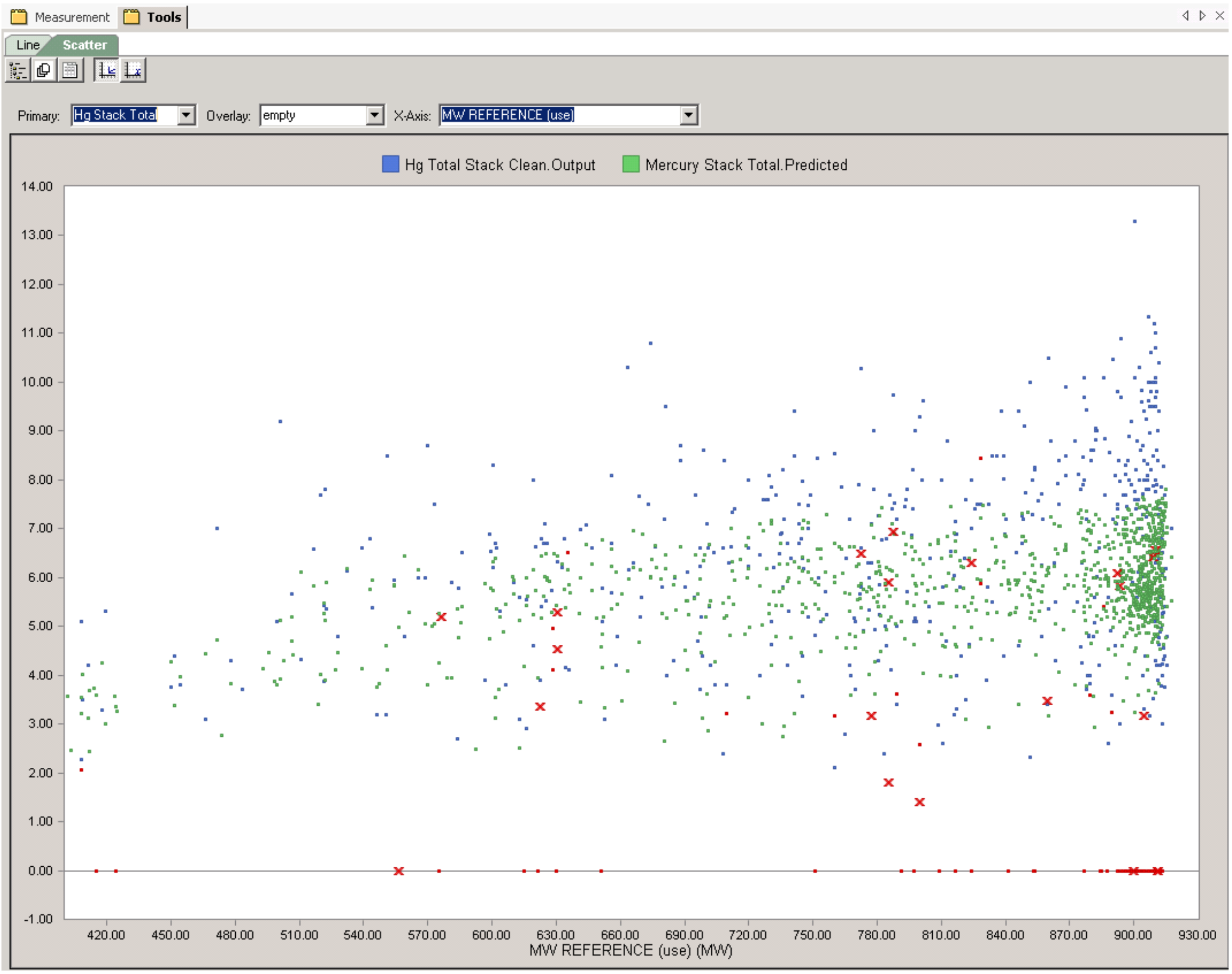

Figure 44: Model Predicted & Actual Hg Stack Total vs. Load for 520 Days

In Figure 44, blue data represent actual measurements that were cleaned and validated and available to train the VOA. Red data represent data that were collected but evaluated as bad. Green is the VOA prediction of what actual would have been (y-axis is µg/m^3).

Figure 45: Sensitivity Analysis of Hg Removal

Figure 45 shows a sensitivity analysis (partial derivatives) of model predicted Hg removal with respect to each of its inputs. Sensitivity to the right of the center-line means a 1 to1 directional relationship. In other words an increase in the value of the input can be expected to result in an increase in the modeled output. Sensitivity to the left of the center line means the directional relationship is 1 to -1 or inverse. This means an increase in the input can be expected to cause the opposite response in the output. Note in this case there is a fuel blend input in the input space of this model, meaning this model is not blind to the effects of fuel blend.

Figure 46 through Figure 49 show the model predicted 2D surface (curve) response of Mercury removal as a function of the model's inputs.

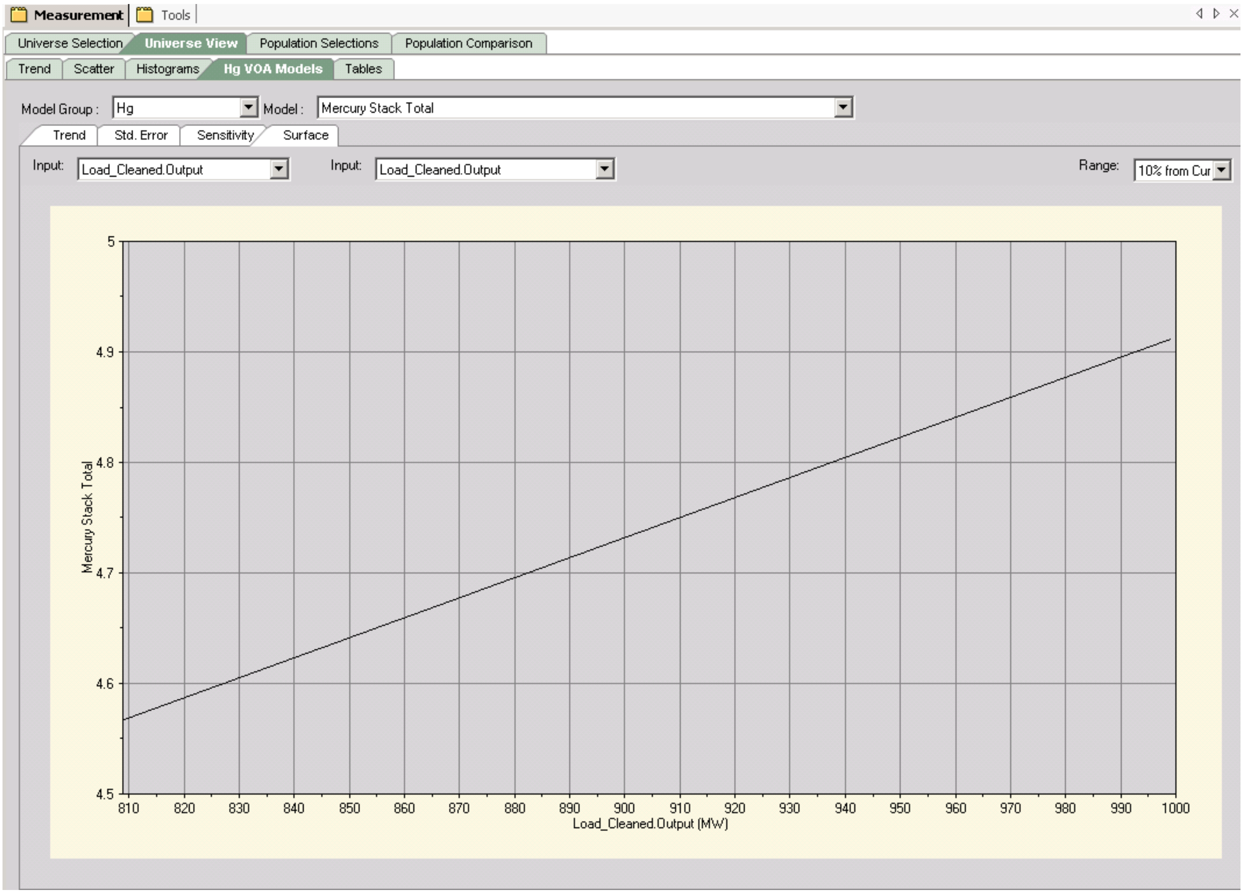

Figure 46: Response Surface Total Stack Hg Model vs. Load

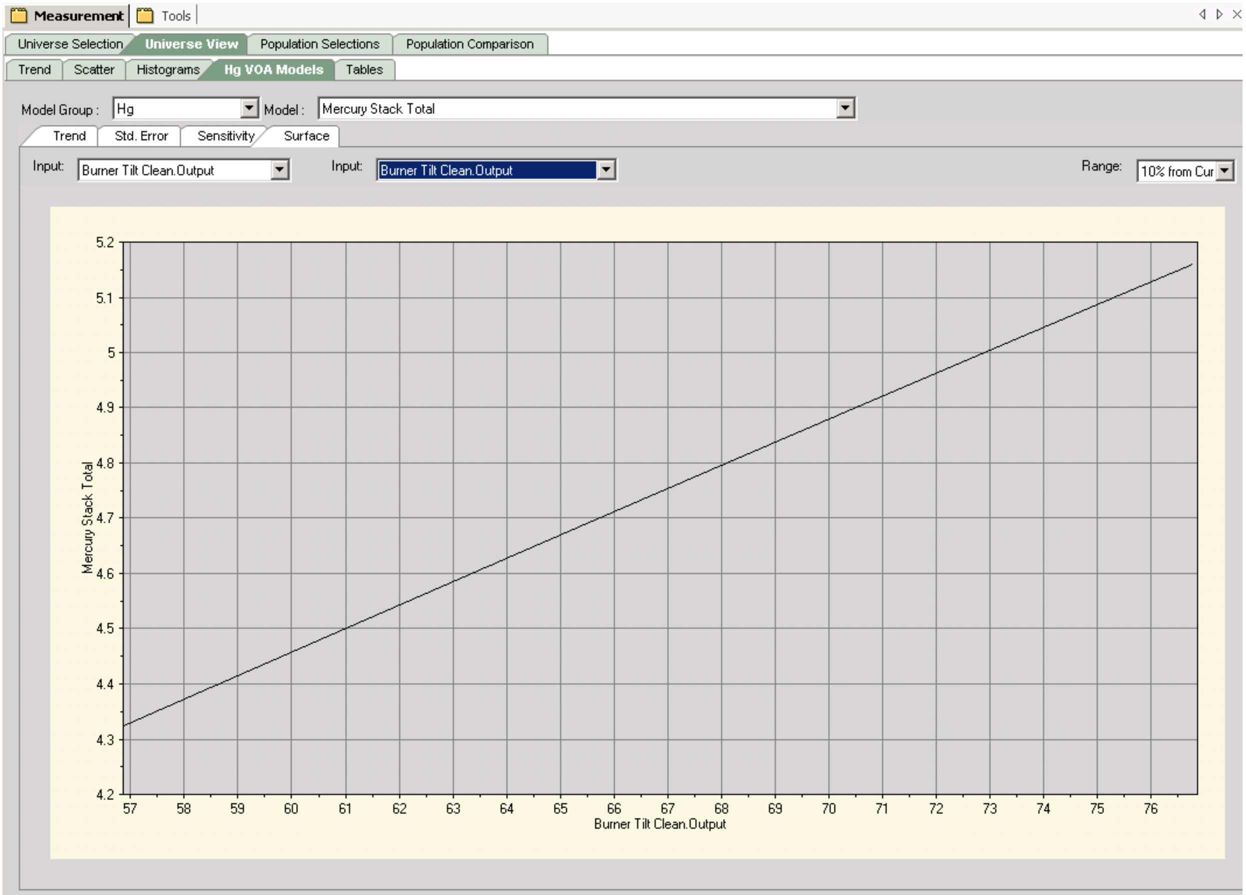

Figure 47: Response Surface Total Stack Hg Model vs. Tilts

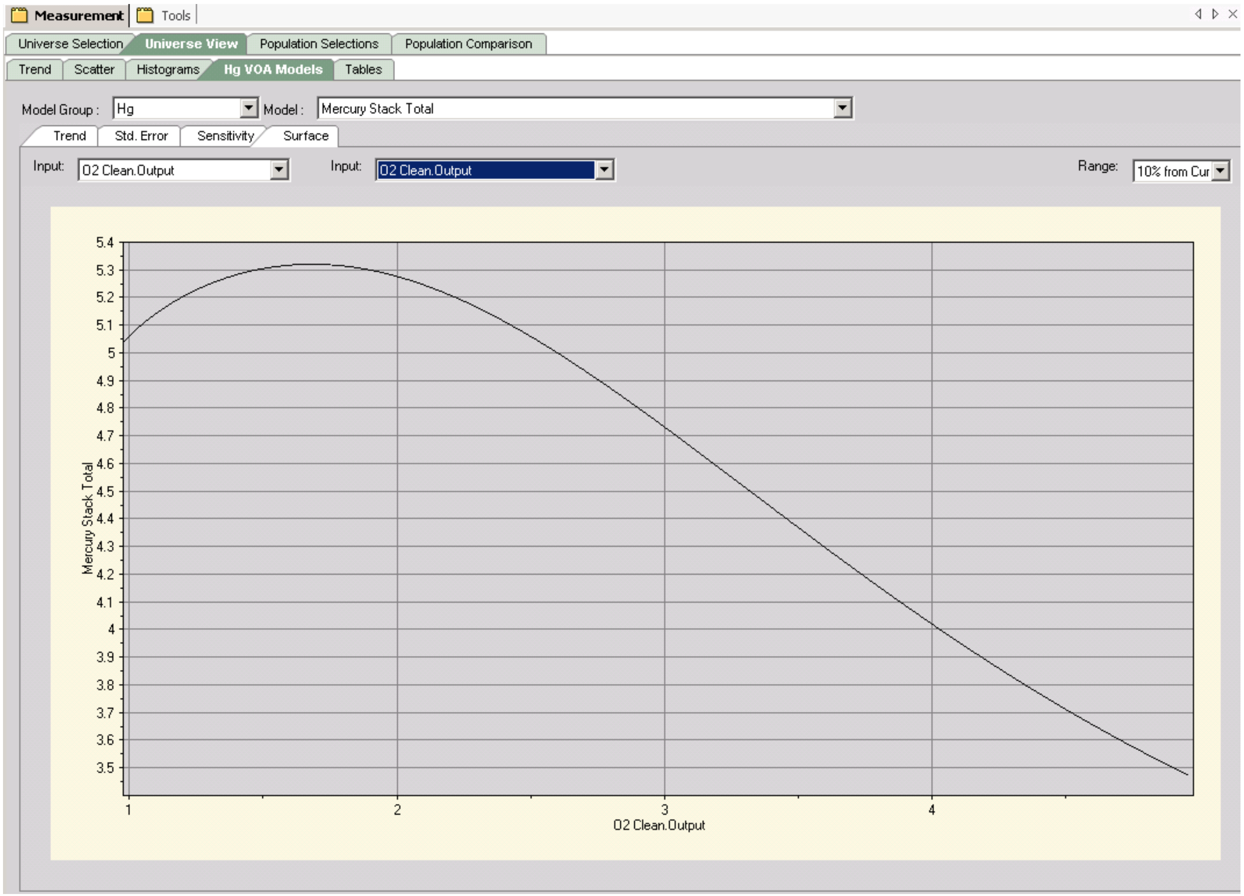

Figure 48: Response Surface Total Stack Hg Model vs. O2

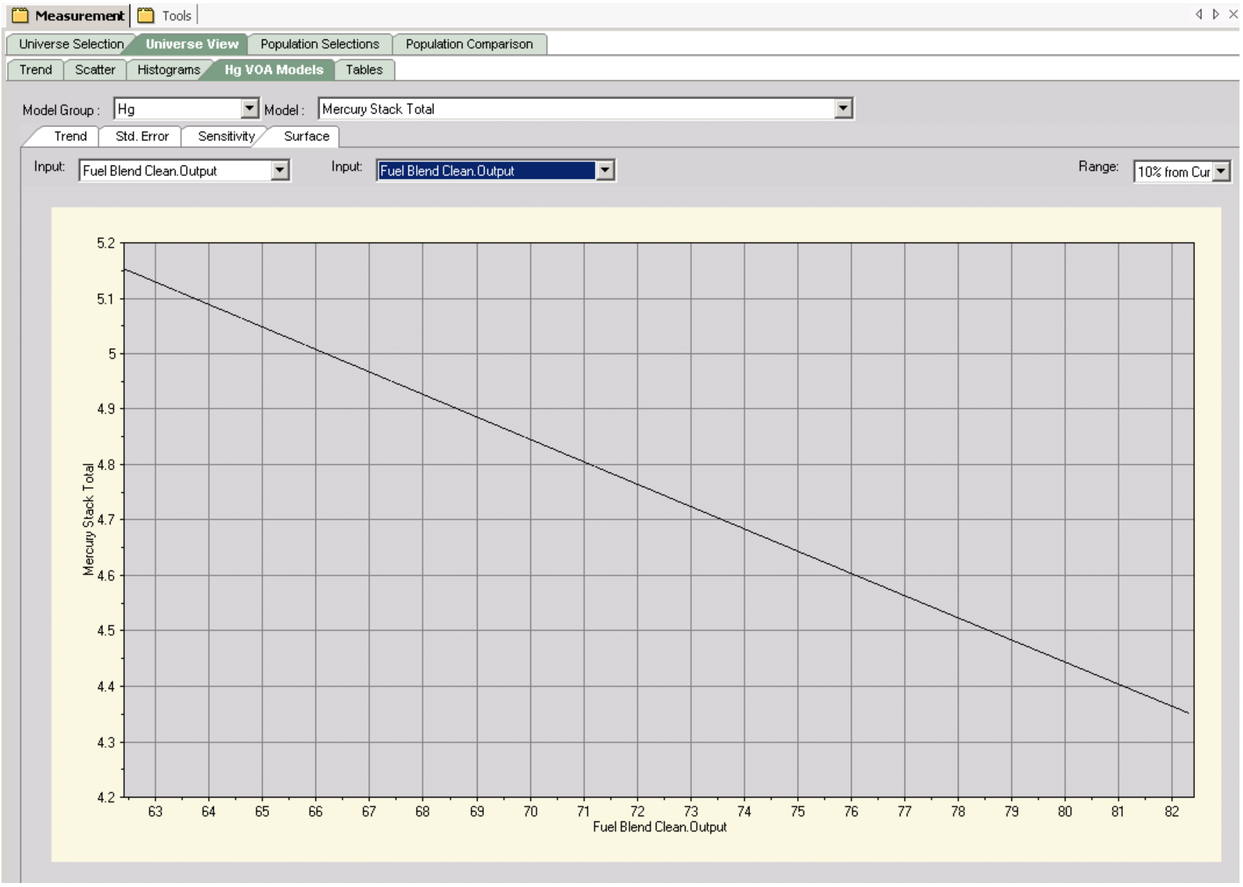

Figure 49: Response Surface Total Stack Hg Model vs. Fuel Blend

3.6 Benefits Analysis

3.6.1 Methodology

Data for the project were analyzed using the following methods:

Trends and Correlations: First an examination of the trends of selected key plant performance indicators was used to provide a picture of how real plant performance has changed over time due to any and all causes. An examination of correlation between these trends was also conducted to look for clues as to what may or may not have caused the movement observed. Data for the entire demonstration period as well as data used for Comparison of Populations (more recent) were examined. As a way of estimating the effect of optimization, key values were plotted against indices of optimizer utilization.

Comparison of Populations: Second, a comparison of selected control and experimental populations was used to measure differences in performance in key dimensions due to one factor – that factor being optimization. Where disturbances could not be removed from or equalized in both populations, models of the KPI's that would be affected by those disturbances were used to estimate the non-disturbance driven difference.

The plots shown are from screen grabs of ProcessLink's on-line analytics tool set. The tools shown were built to support the highly interactive and iterative process of cleaning, selecting, viewing and analyzing large multi-variable datasets. The plots shown include time series trends, concatenated time indexed trends (non continuous time series), scatter plots and histograms. Tabulated summaries of means are also presented.

3.6.2 Long Term Trends and Correlations

Unless specified, the plots in the following sections (Figure 50 through Figure 74) show 1,500 data points from 1/20/09 through 6/25/2010, roughly corresponding to the Demonstration period. Data was filtered to include only samples where load was above 880MW. In the trend plots, these data points were ordered by time (x-axis). Note these are not continuous time-series. In the scatter plots, they are plotted versus an index of optimizer utilization.

Selection of a MW range for analysis is an effective way of removing the most significant disturbance from a population since MW output is the single largest cause of variability for almost all plant signals. Holding actual unit load steady over statistically significant time periods for all relevant variances is not feasible. It can easily be done in the analysis however, making movement not due to load, much easier to see. A justification for the load range selected is also provided.

The exclusion of early January data from 2009 is largely due to a lack of both good Hg data and PCT PRB data from that time.

3.6.2.1 Unit Load

Figure 50 shows the unfiltered unit load trend for the entire Demonstration period (1/20/09 – 6/25/10). Observed events in this trend include spring outages from 2009 and 2010. The 2010 outage was 30 days in duration. Some data for some signals is missing for the summer of 2009 due to the renovation of some data collection architecture.

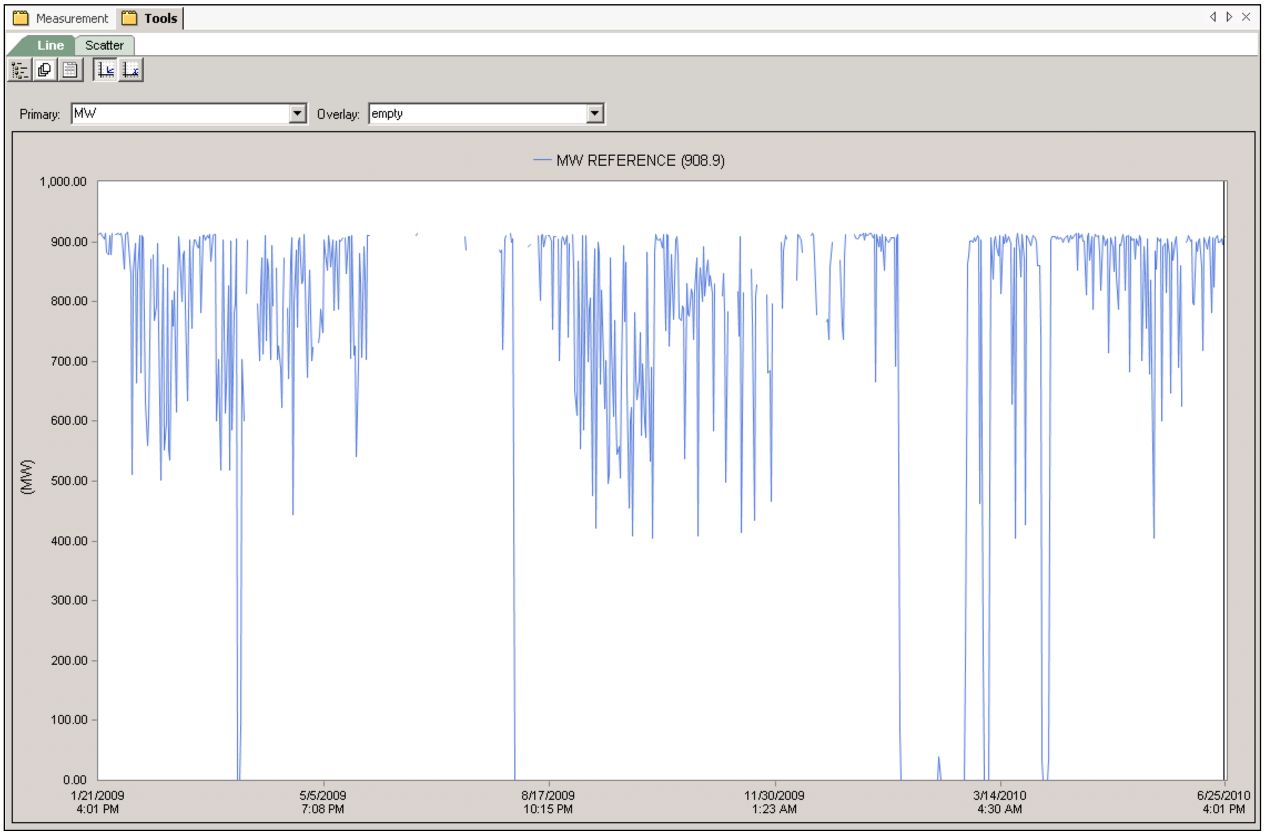

Figure 50: Unfiltered Unit Load 1/20/09-6/25/10

Figure 51 shows the unfiltered distribution of MW for the entire Demonstration period. The load distribution shows that LMS U2 is a semi base loaded unit, with more than 40% of its operation domain in the top 5% of the load range.

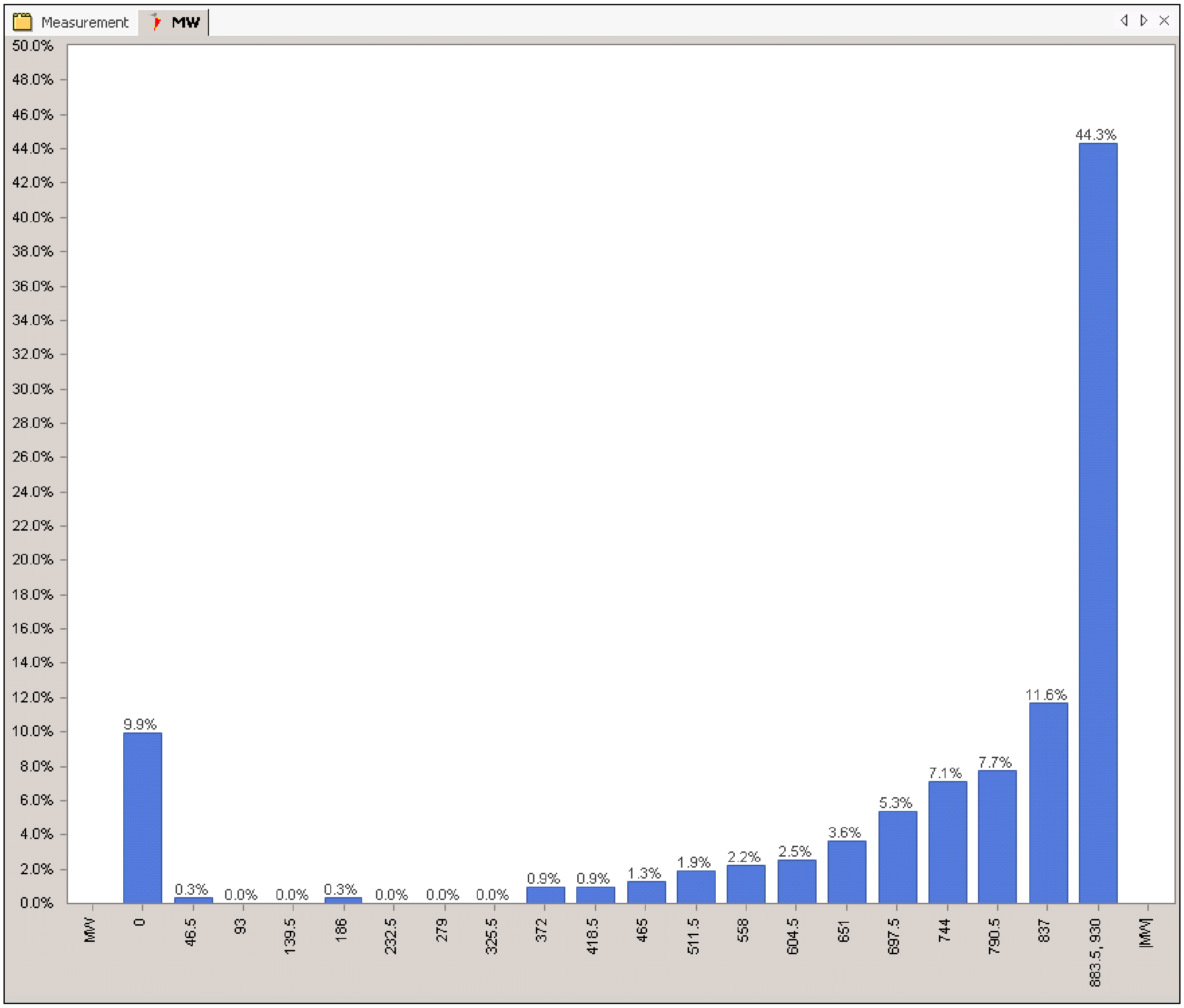

Figure 51: Unfiltered Unit Load Distribution 1/20/09-6/25/10

Figure 52 shows the concatenated time indexed dataset (TID) resulting from the selection of all samples from the Demonstration period (1/20/09 – 6/25/10) where unit load was above 880 MW. This represents the data analyzed in the following section looking at "Long Term Trends and Correlations".

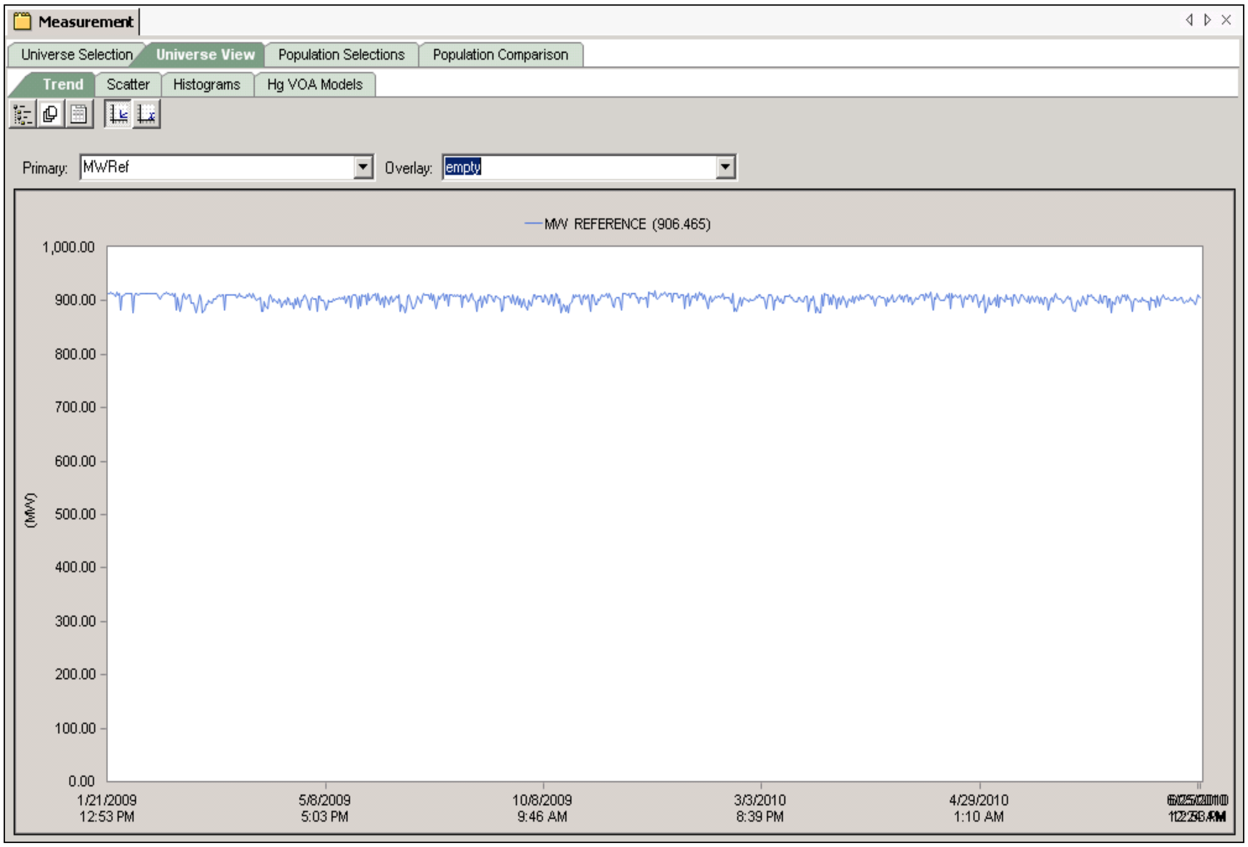

Figure 52: Filtered Unit Load, MW>880, 1/20/09-6/25/10

Figure 53 shows the distribution of unit load in the TID selected for analysis, in the dimension of unit load. All samples where unit load is less than 880 MW have been filtered out. Of the data remaining more that 70% represent operation where unit load is between 900 and 920 MW, with the largest portion in the range between 905 and 910 MW.

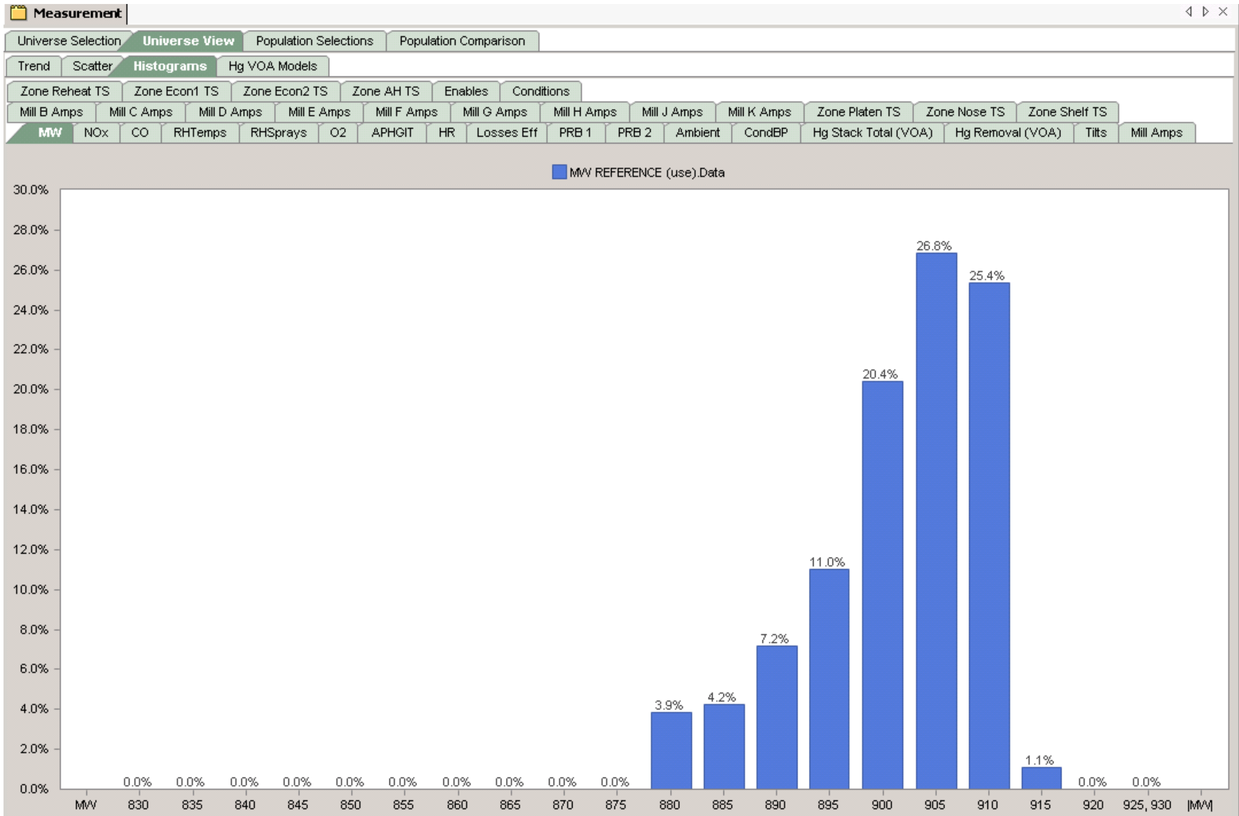

Figure 53: Unit Load Distribution >880 MW 1/20/09-6/25/10

3.6.2.2 PRB Blend

Over the course of the Demonstration period the fuel blend for LMS U2 was transitioned from 70/30 Lignite/PRB blend to a ratio closer to 50/50, with the permanent switch to PRB happening at the beginning of 2010. The trend in Figure 54 shows the blend setpoint from the CoalFusion fuel blending system. Though early 2009 data for blend was not available and this region was excluded in the later comparison of means, for purposes of visual inspection the average blend was around 30% PRB over this interval.

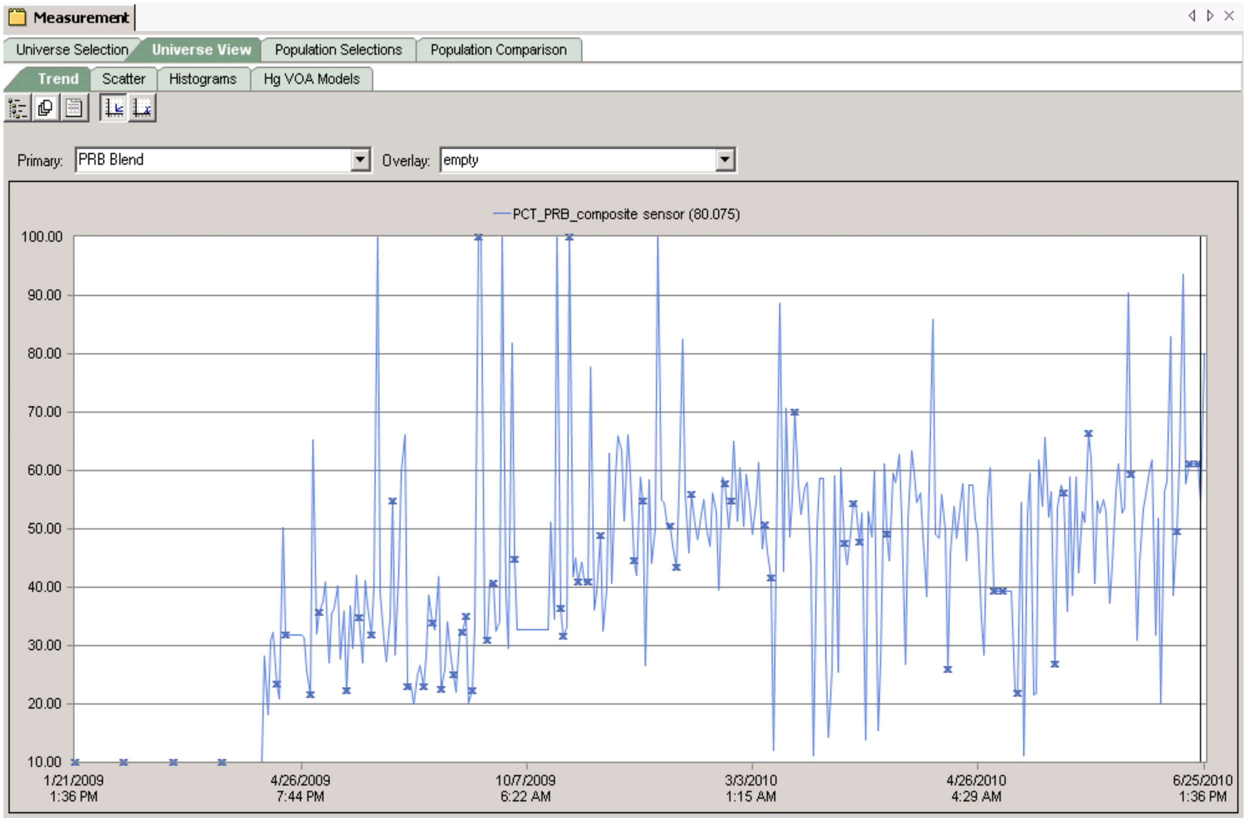

Figure 54: PCT PRB Blend, MW >880, 1/20/09-6/25/10. Y-Axis is % PRB

3.6.2.3 Mercury Removal and Stack Total VOA Predictions

This section shows the analysis for the data for the long term predictions provided by the VOAs. The objective for Mercury Removal is "Up", for all causes. The objective for Mercury Stack Total is "Down".

3.6.2.3.1 Mercury Removal (VOA)

Figure 55 shows the VOA-predicted Mercury Removal. The spikes are artifacts due to the presence of O2 calibration periods in the data the model was being queried over. These samples were filtered out for comparison of means.

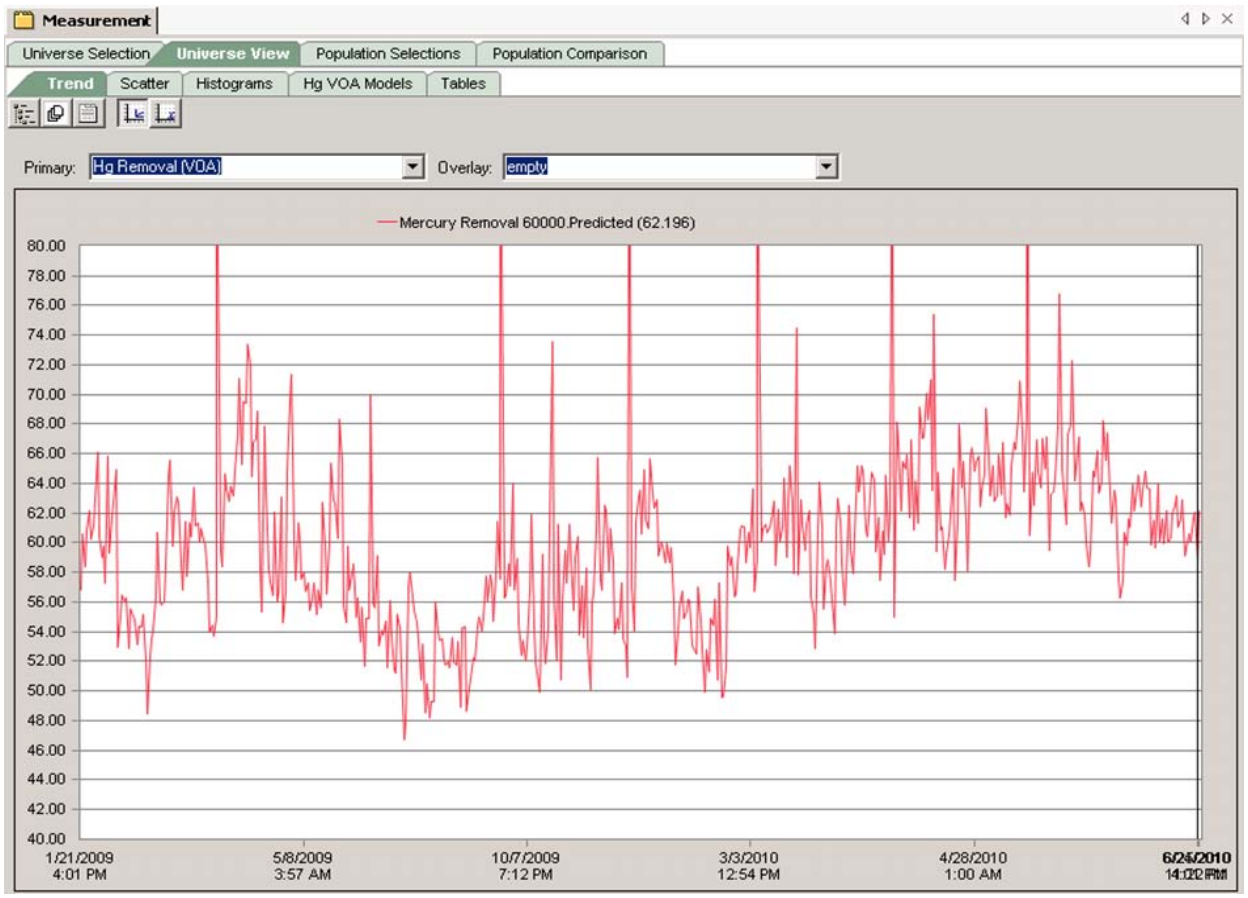

Figure 55: Hg Removal (VOA Model Prediction) MW>880, 1/20/09-6/25/10

Figure 56 shows the VOA prediction of Mercury Removal vs. PCT PRB. No input for fuel blend existed in this model and the expectation was that no causal relationship would be seen.

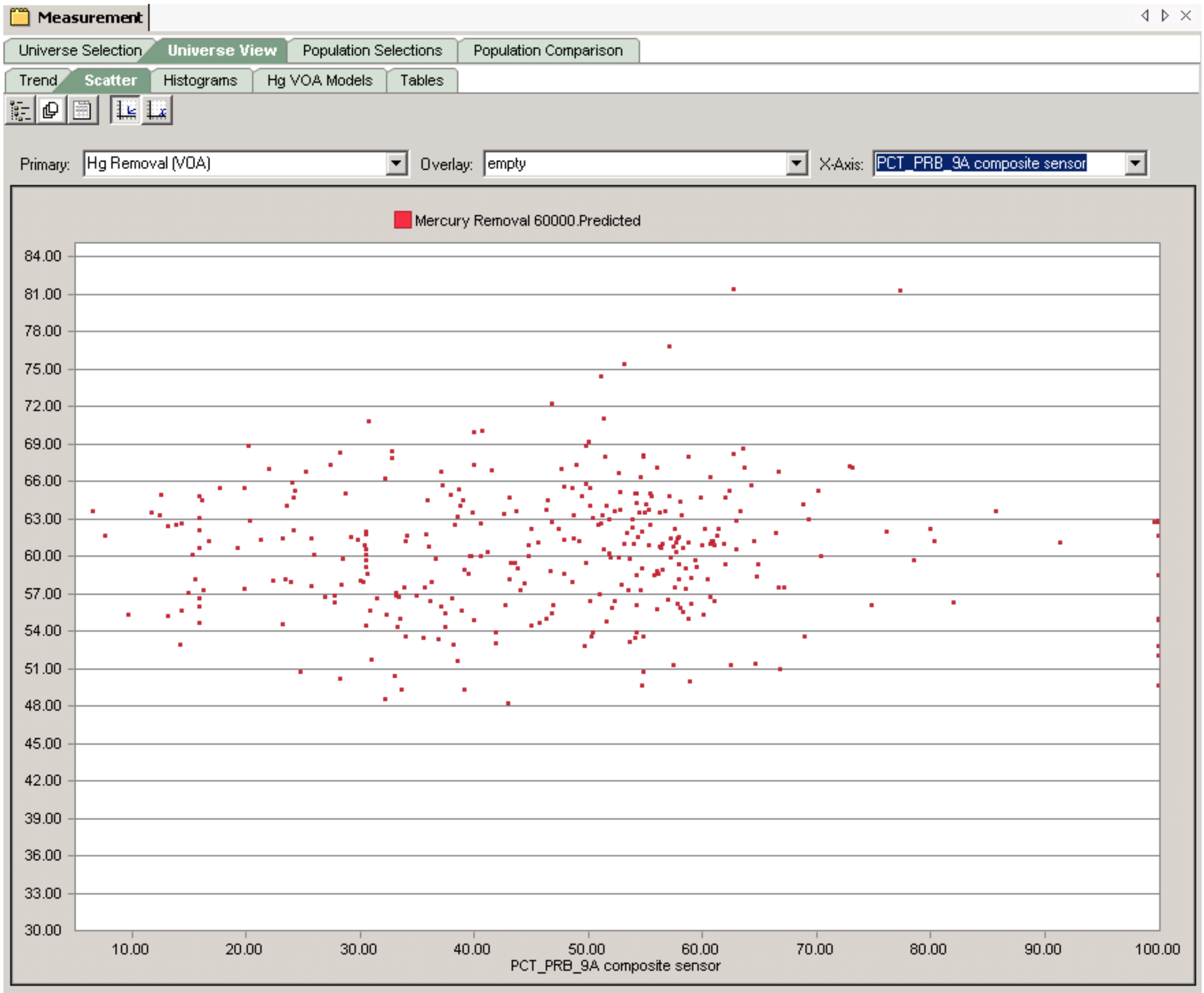

Figure 56: Hg Removal (VOA Model Prediction) vs. PCT PRB Blend, MW > 880, 1/20/09-6/25/10

Figure 57 shows VOA-predicted Mercury Removal along with an index of utilization that provides a rough measure of to what degree optimization is active at a given time. Higher values of utilization index indicate more optimization was occurring. Utilization and Removal both vary over the period analyzed.

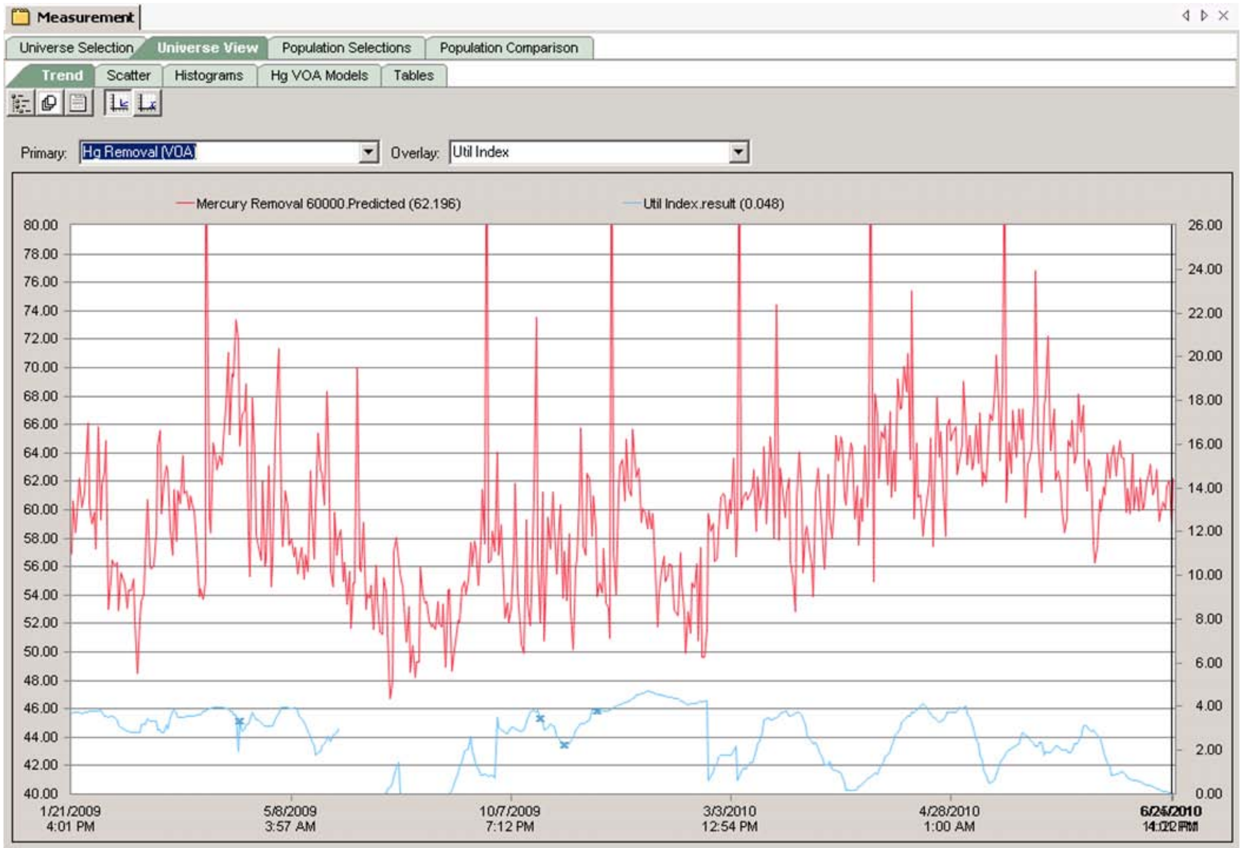

Figure 57: Hg Removal (VOA Model Prediction0 and Utilization Index, MW>880, 1/20/09-6/25/10

Figure 58 shows VOA-predicted Mercury Removal plotted against the utilization index. No clear relationship was seen.

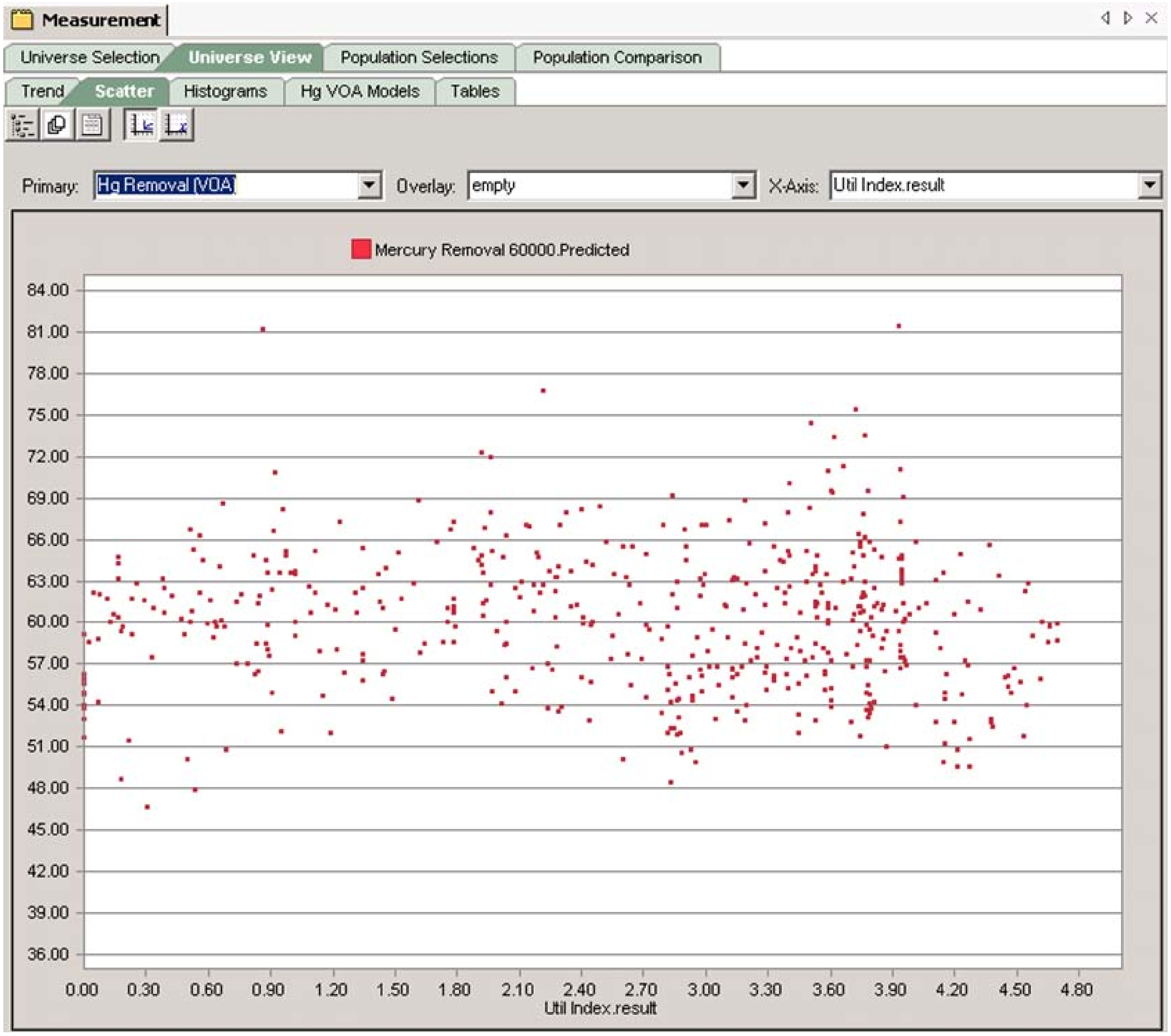

Figure 58: Hg Removal (VOA Model Prediction) vs. Utilization Index, MW>880, 1/20/09-6/25/10

3.6.2.3.2 Mercury Stack Total (VOA)

Figure 59 shows the VOA-predicted Mercury Stack Total. A clear trend was seen.

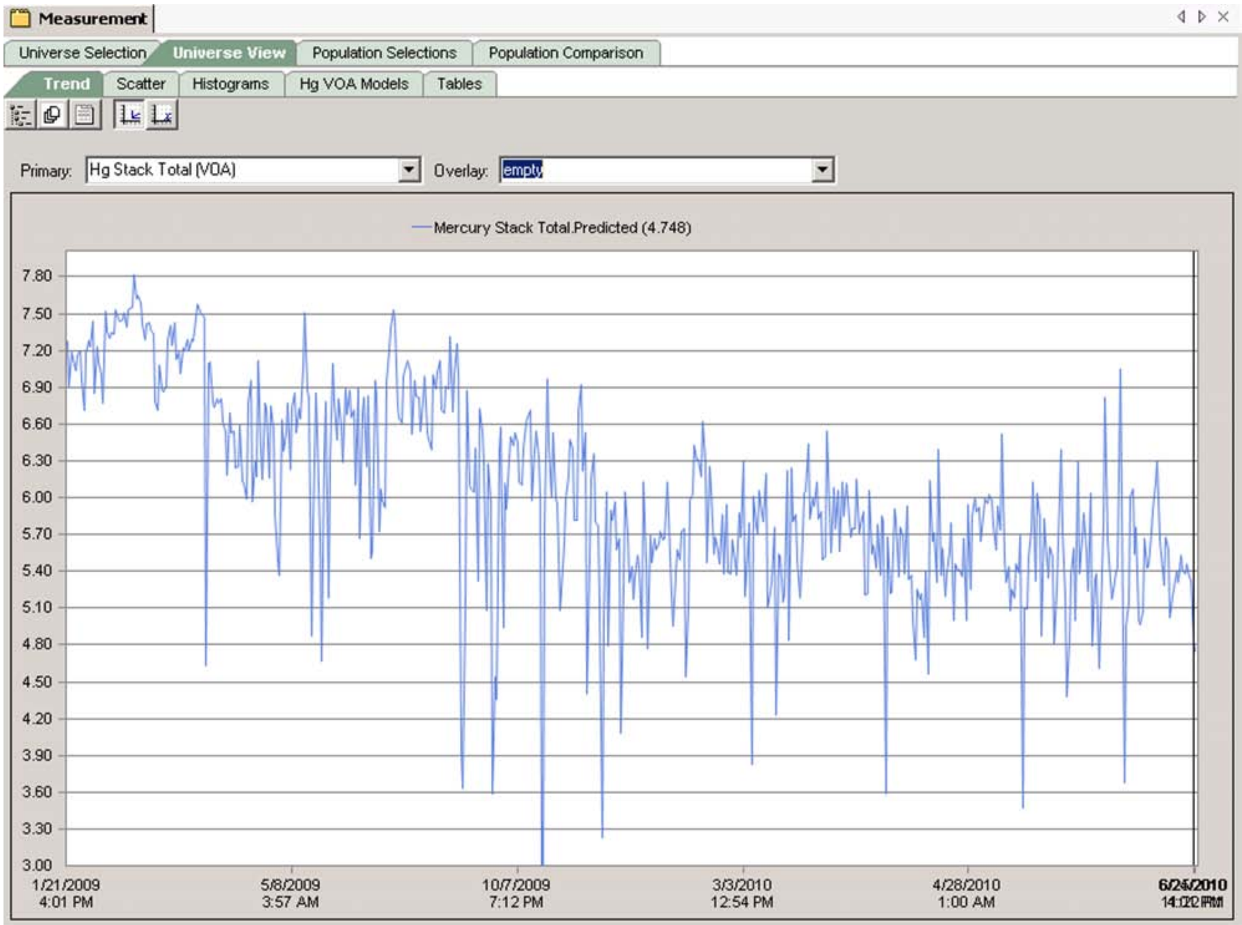

Figure 59: Hg Stack Total (VOA Model Prediction), MW>880, 1/20/09-6/25/10

Next, predicted Mercury Stack Total compared to fuel blend was plotted. A clear inverse correlation is seen in Figure 60.

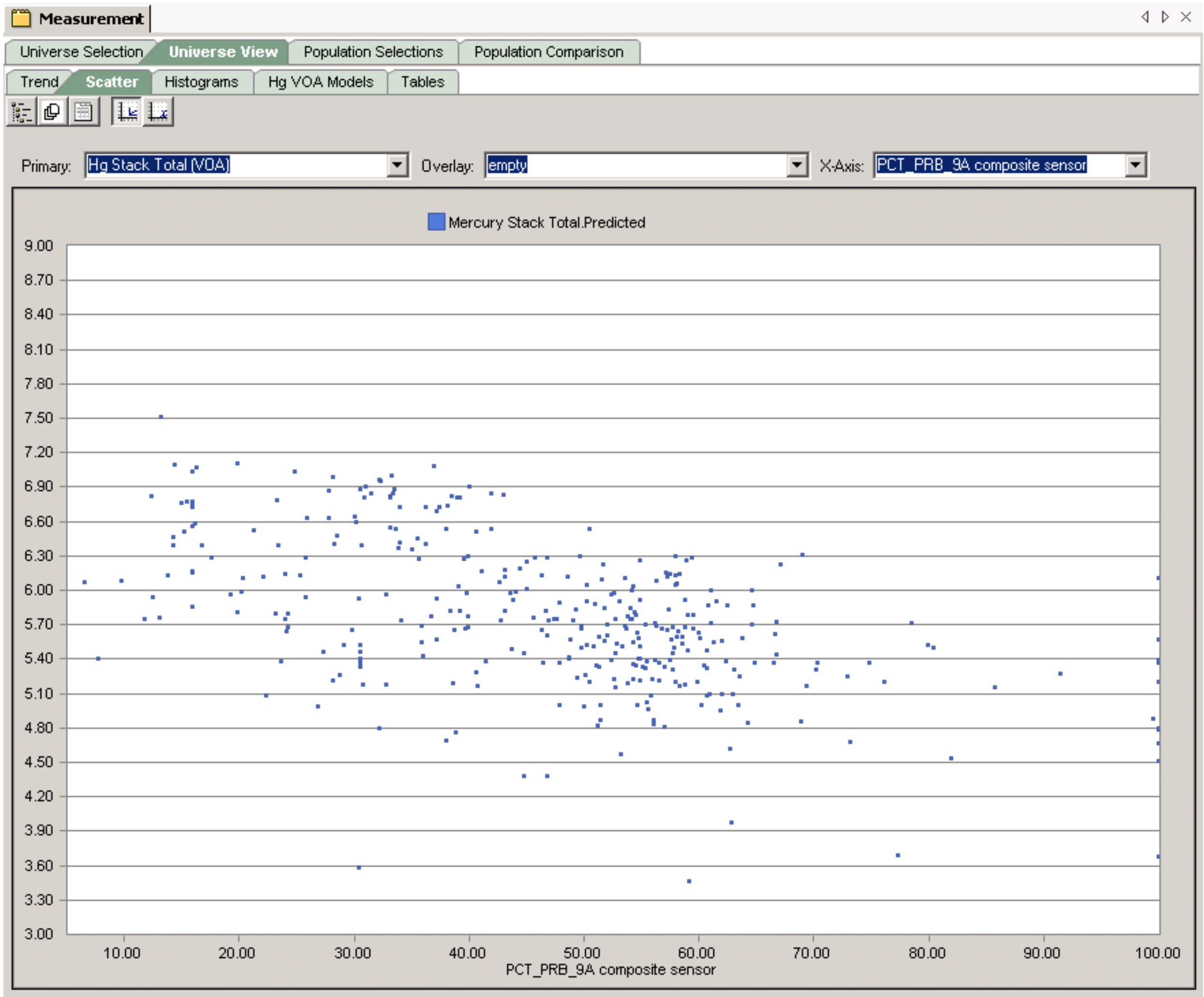

Figure 60: Hg Stack Total (VOA Model Predicted) vs. PCT PRB Blend, MW>880, 1/20/09-6/25/10

Figure 61 shows Predicted Mercury Stack Total along with the utilization index.

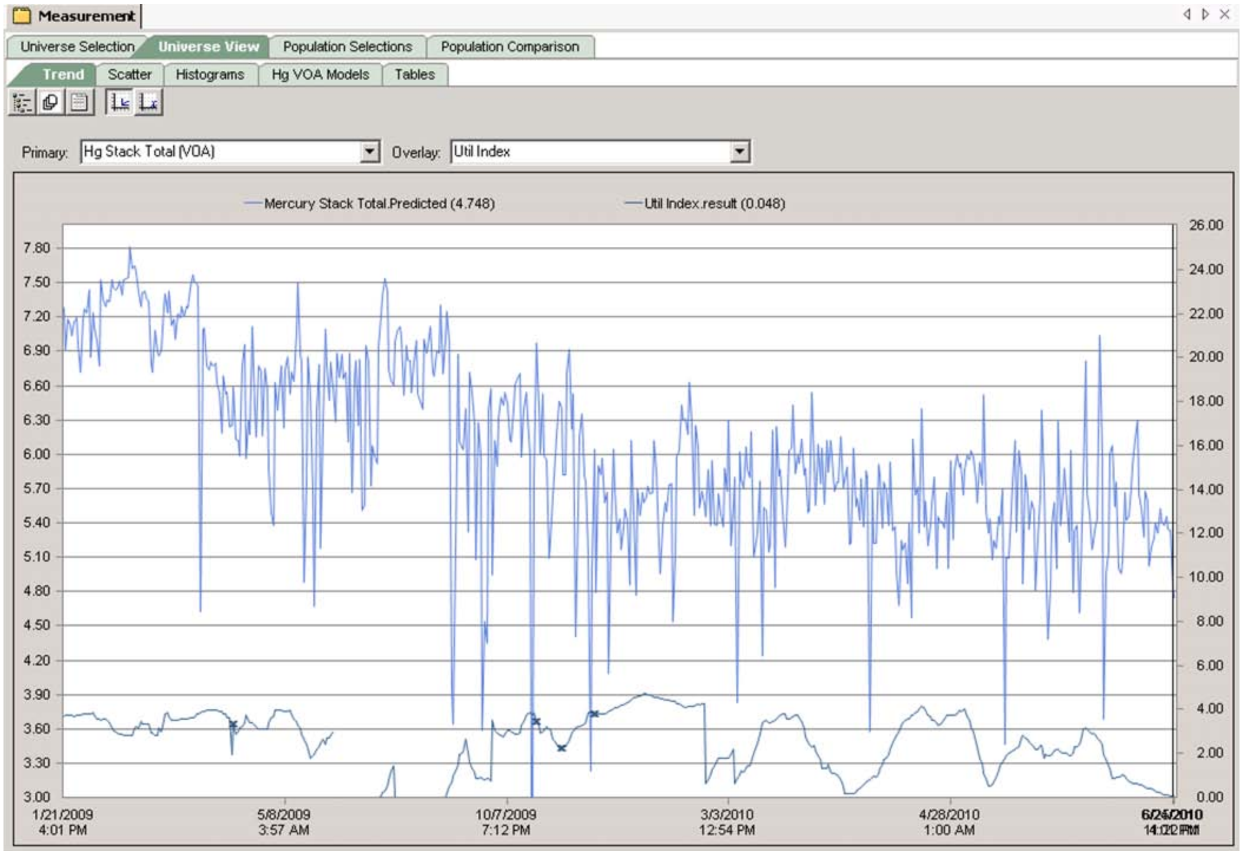

Figure 61: Hg Stack Total (VOA Model Prediction) and Utilization Index, MW>880, 1/20/09-6/25/10

Figure 62 plots the VOA Predicted Mercury Stack Total vs. utilization index. No clear relationship was seen. Note: y axis is µg/m^3.

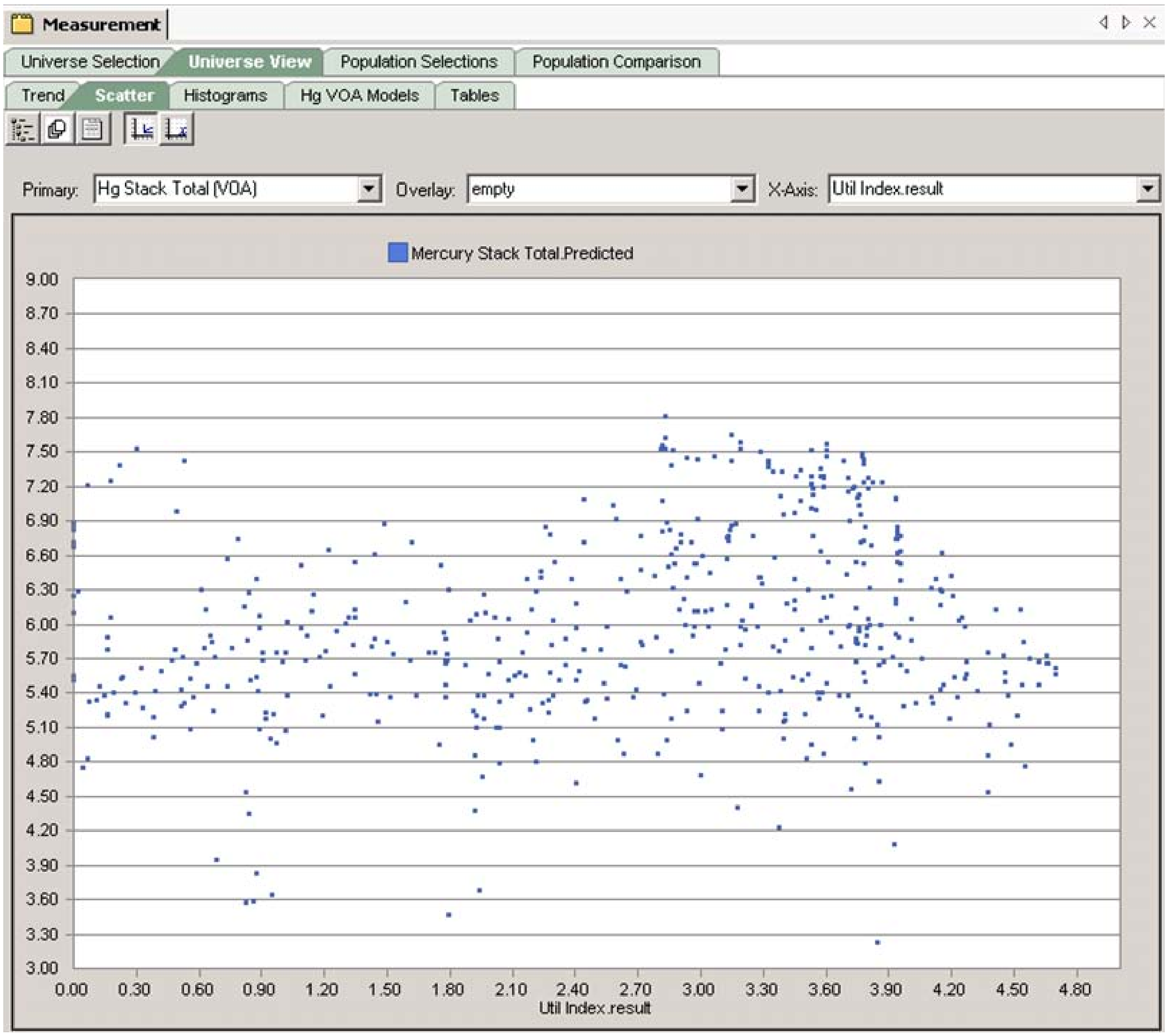

Figure 62: Hg Stack Total (VOA Model Prediction) vs. Utilization Index, MW>880, 1/20/09-6/25/20

3.6.2.4 NOx

This section examines the long term trends and correlations for CEMS NOx. The objective for NOx is “Down”.

Figure 63 shows NOx over the Demonstration period (1/20/09 – 6/25/10).

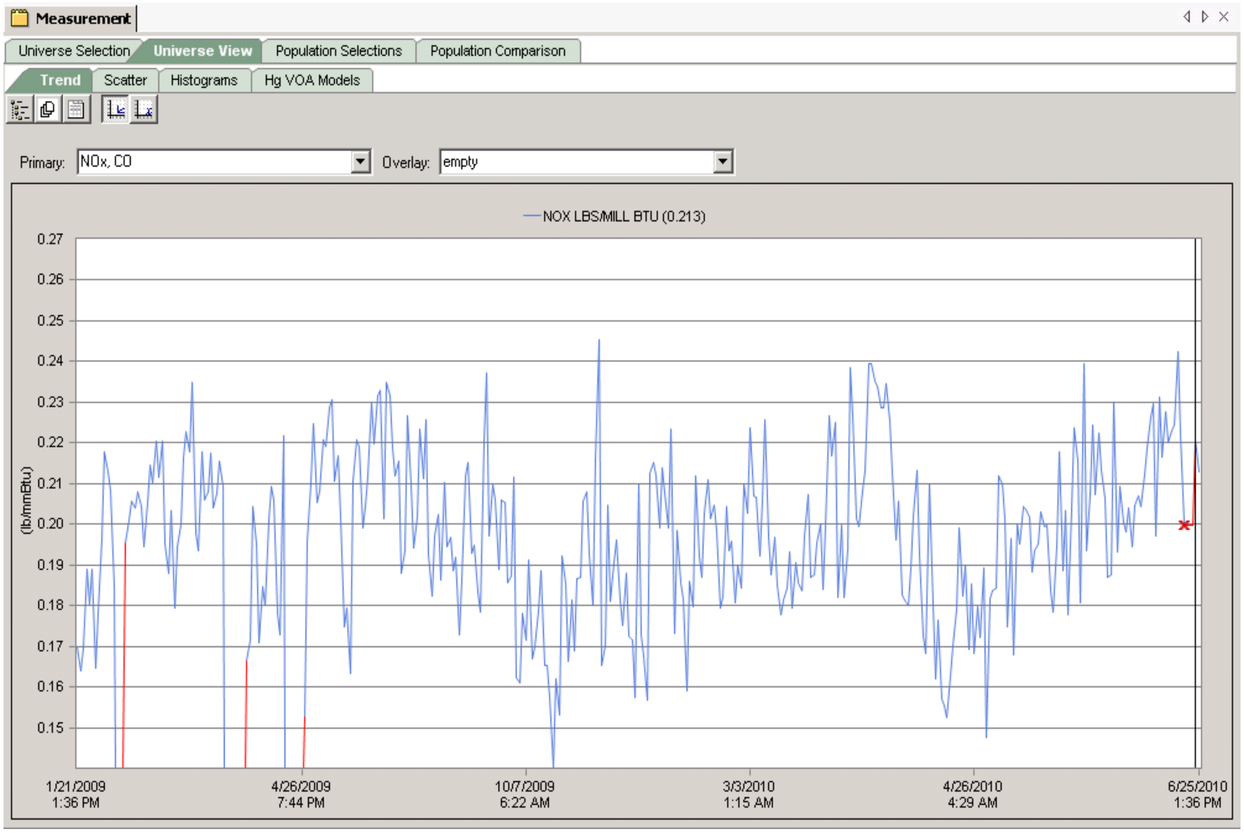

Figure 63: NOx Emission Rate, MW>880, 1/20/09-6/25/10

Figure 64 shows NOx plotted vs. utilization. An inverse correlation was seen.

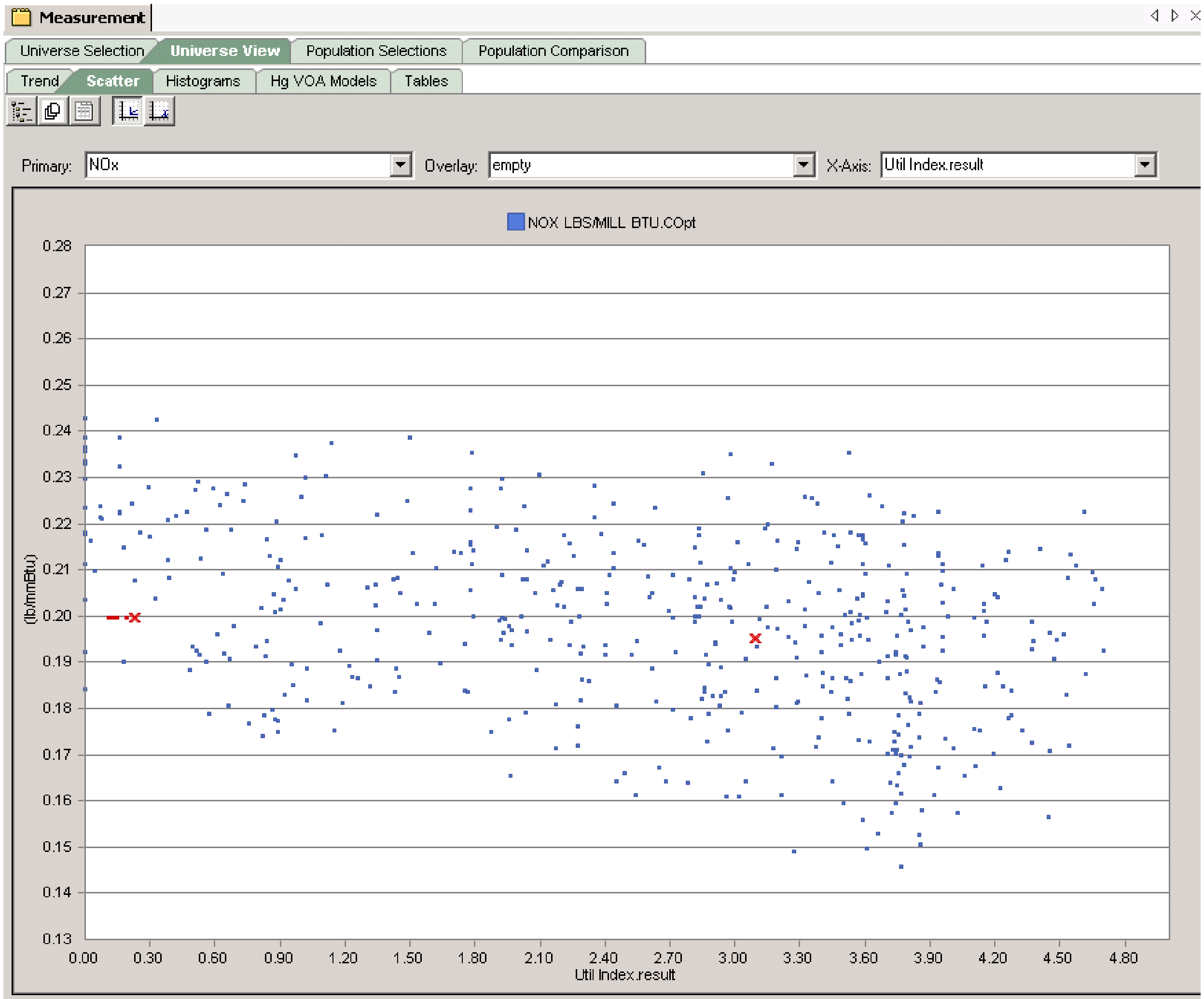

Figure 64: CEMS NOx vs. Utilization Index

Figure 65 shows PRB blend plotted vs. utilization. No clear relationship was seen. Lignite fuel has higher Nitrogen content than PRB fuel. If an inverse relationship should be seen, it would indicate that periods of higher utilization coincide with periods of lower PRB percentage, which would bias NOx higher.

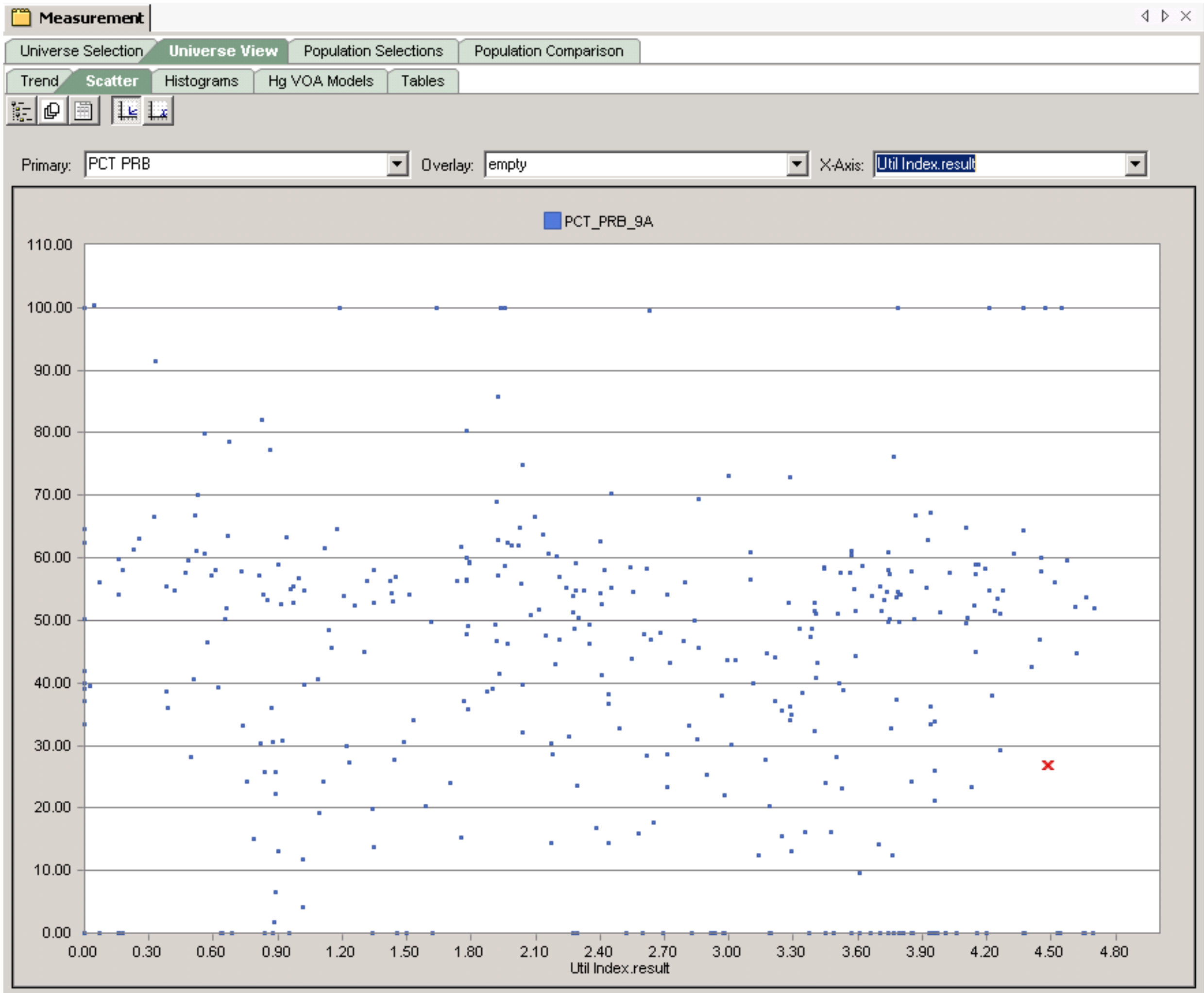

Figure 65: PRB Blend vs. Utilization Index

3.6.2.5 CO

The objective was to keep CO below 40ppm as indicated in Figure 66 and Figure 67. Although increased variability was seen with increasing utilization as seen in Figure 67, CO was generally held below the desired limit.

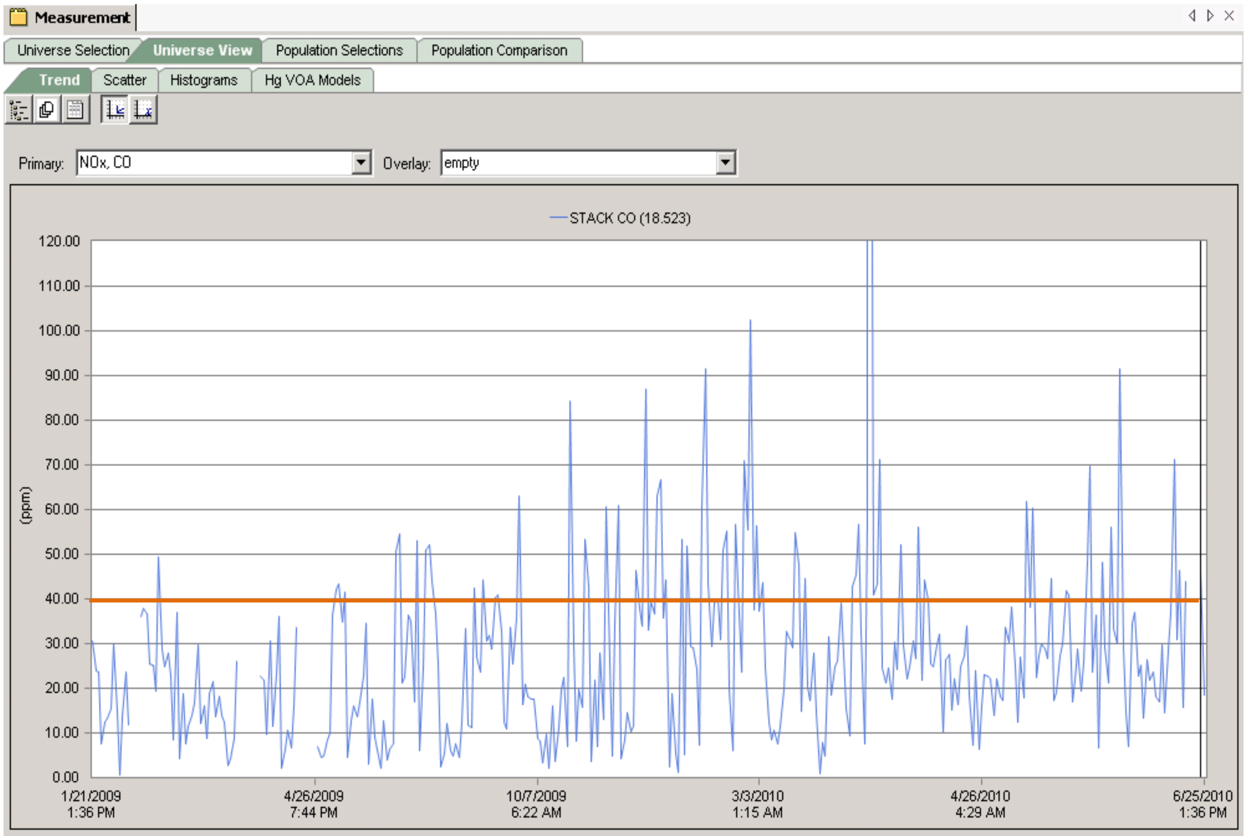

Figure 66: CO Emission Rate, MW>880, 1/20/09-6/25/10

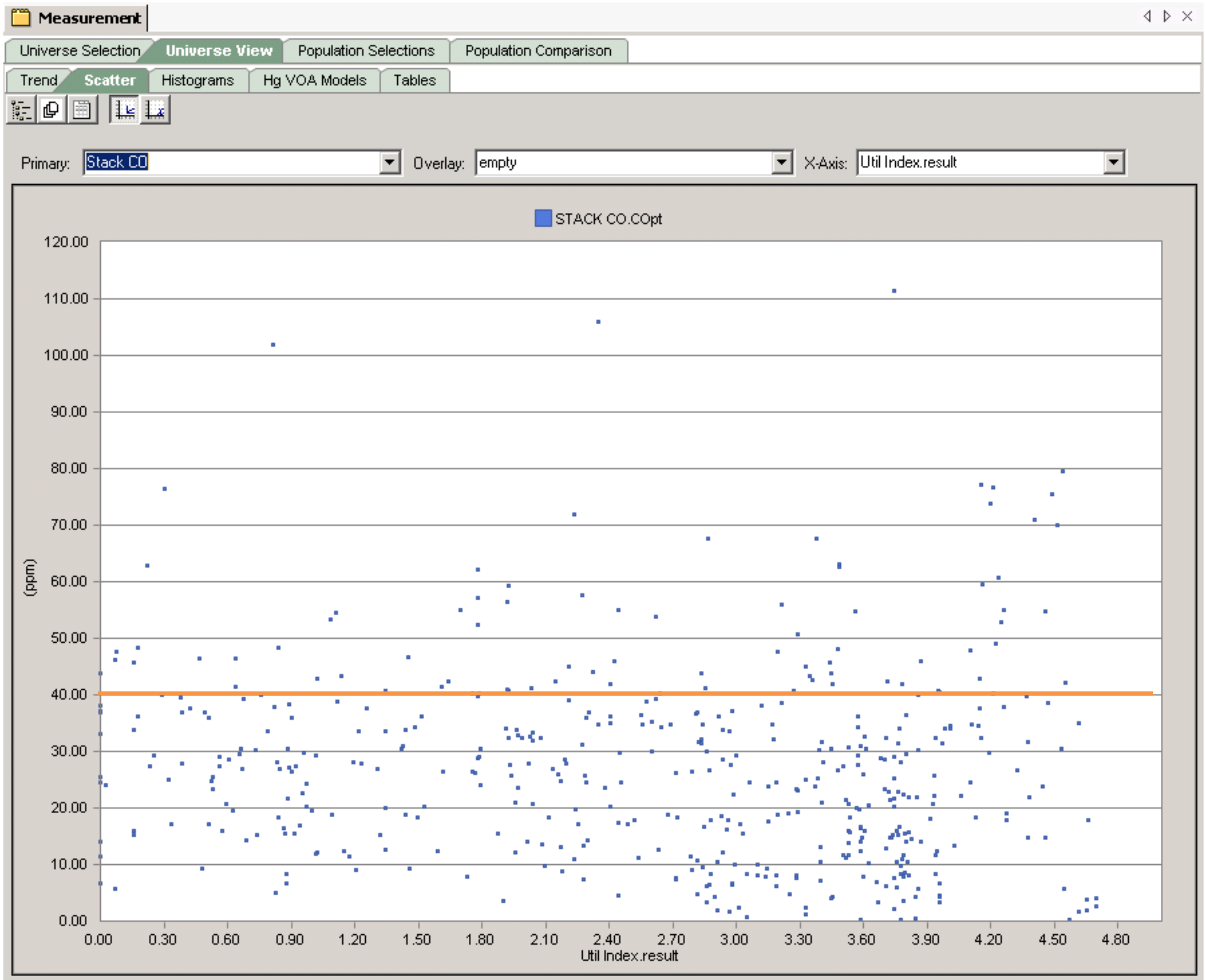

Figure 67: CEMS CO vs. Utilization Index

3.6.2.6 RH Steam Temps

The objective was to keep Reheat Steam Temperatures (RH temps) above 980 degF as indicated in Figure 68 and Figure 69. Burner tilts control RH temps by raising and lowering the fireball, which affects NOx staging. Typically, lower tilts means lower temps, lower NOx and higher heat rate. Optimization was seen in the degree to which the expected decrease in RH temps was absent. i.e. the trend is flat.

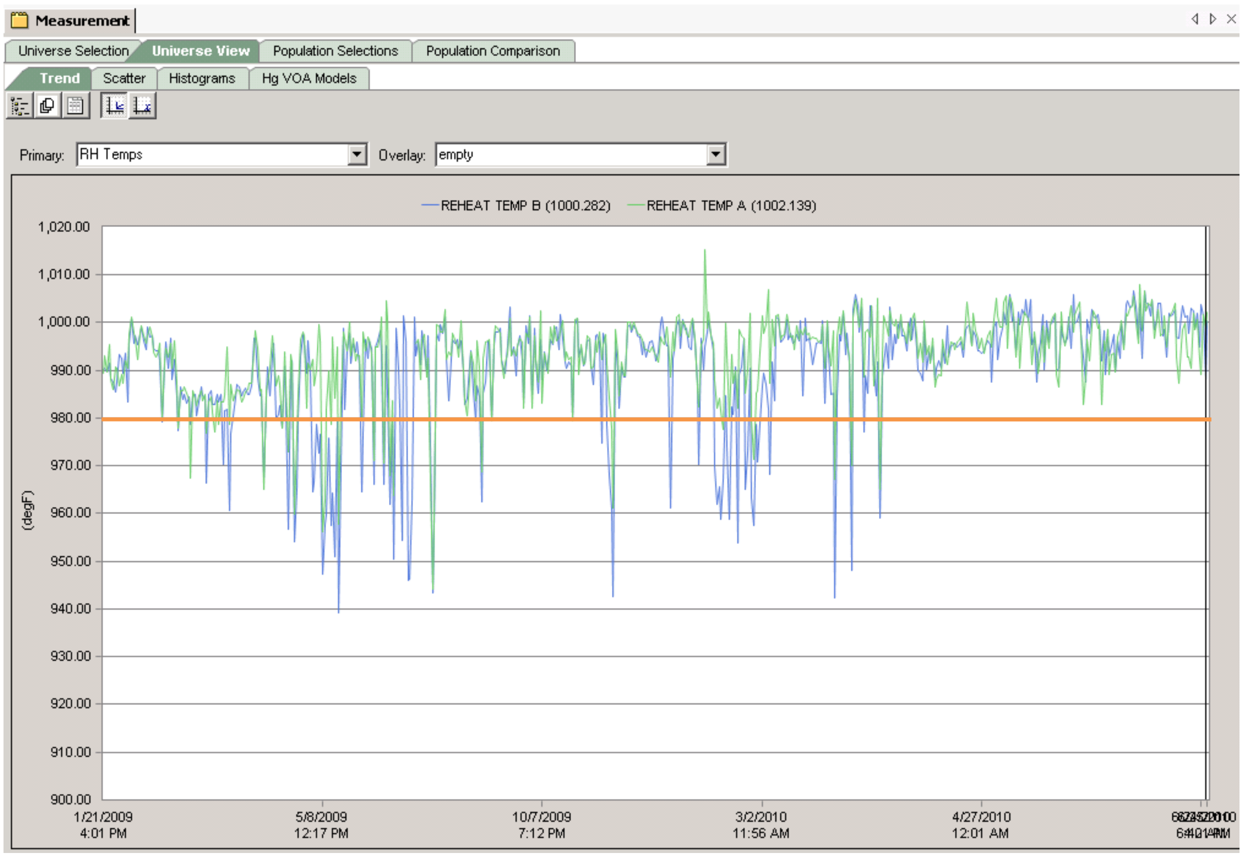

Figure 68: RH Temps, MW>880, 1/20/09-6/25/10

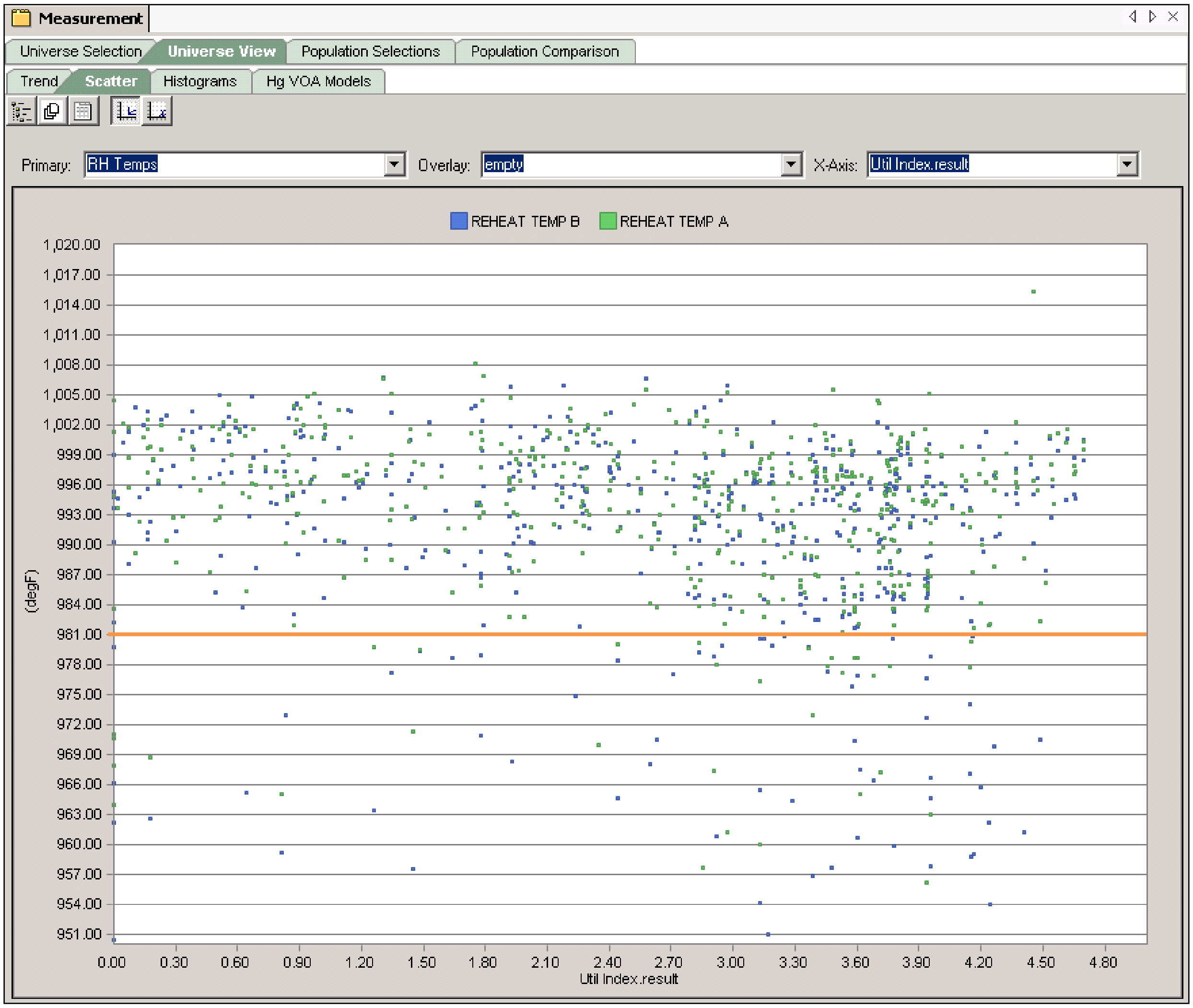

Figure 69: RH Temps vs. Utilization Index

3.6.2.7 O2

The objective was to maintain O2 above 2 % to prevent reducing conditions in the furnace, which contribute to waterwall erosion, as indicated in Figure 70 and Figure 71. The O2 was also maintained above 2% as a precaution since the Stack CO measurement is far downstream and the gas was well mixed, which may not always reflect local conditions well.

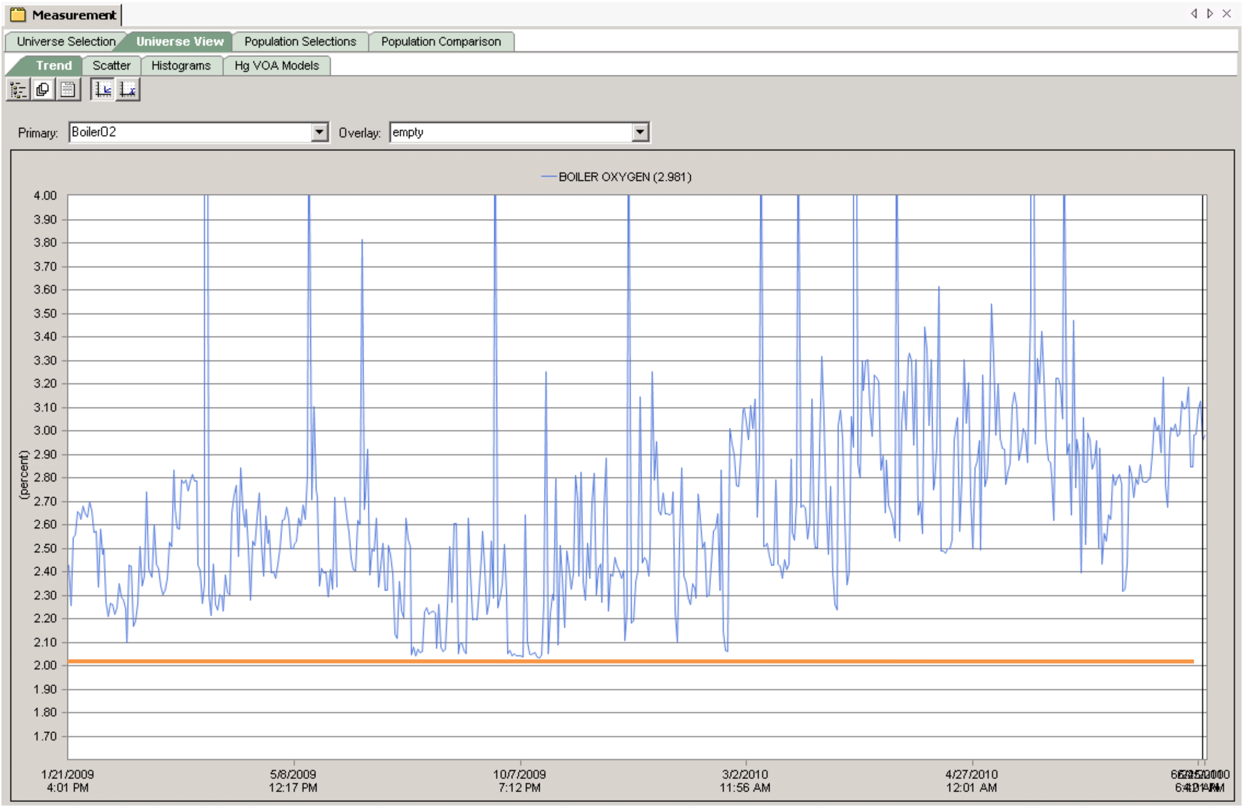

Figure 70: Measured O2, MW>880, 1/20/09-6/25/10

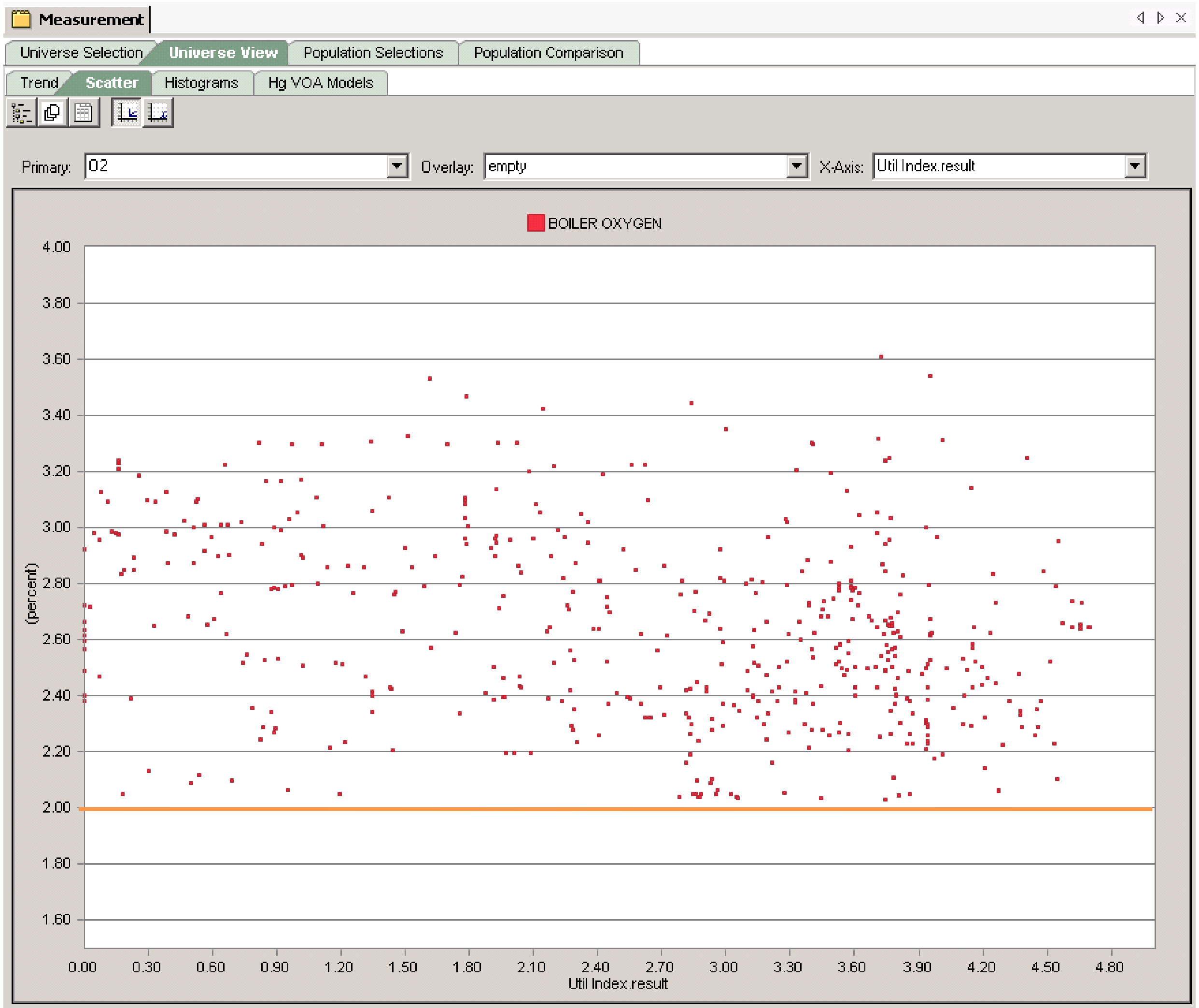

Figure 71: Boiler O2 vs. Utilization Index

3.6.2.8 Air Preheater Gas Inlet Temperature

The objective was to maintain Air Preheater Gas Inlet Temperatures (APHGIT) below 780 degF to protect the air preheater (APH), as indicated in Figure 72 - Figure 74.

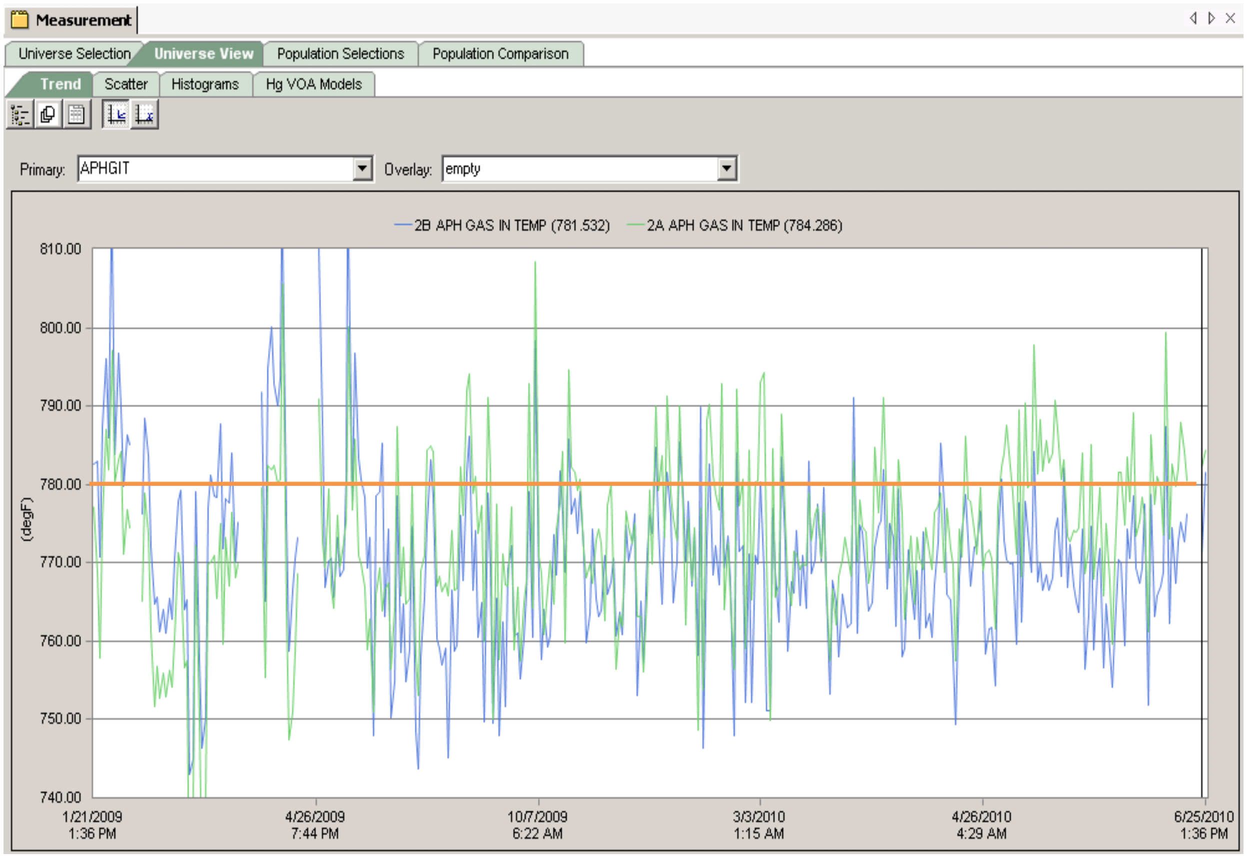

Figure 72: APH Gas Inlet Temps, MW>880, 1/20/09-6/25/10

The APHGIT objective for LMS U2 is aimed at protecting the APH from prolonged high temperature-related material fatigue. This objective was not only an explicit objective of SootOpt, but indirect effects from combustion optimization were possible. The trend for the A sides shown in Figure 73, which ran above 780 fairly often, was downward with increasing utilization.

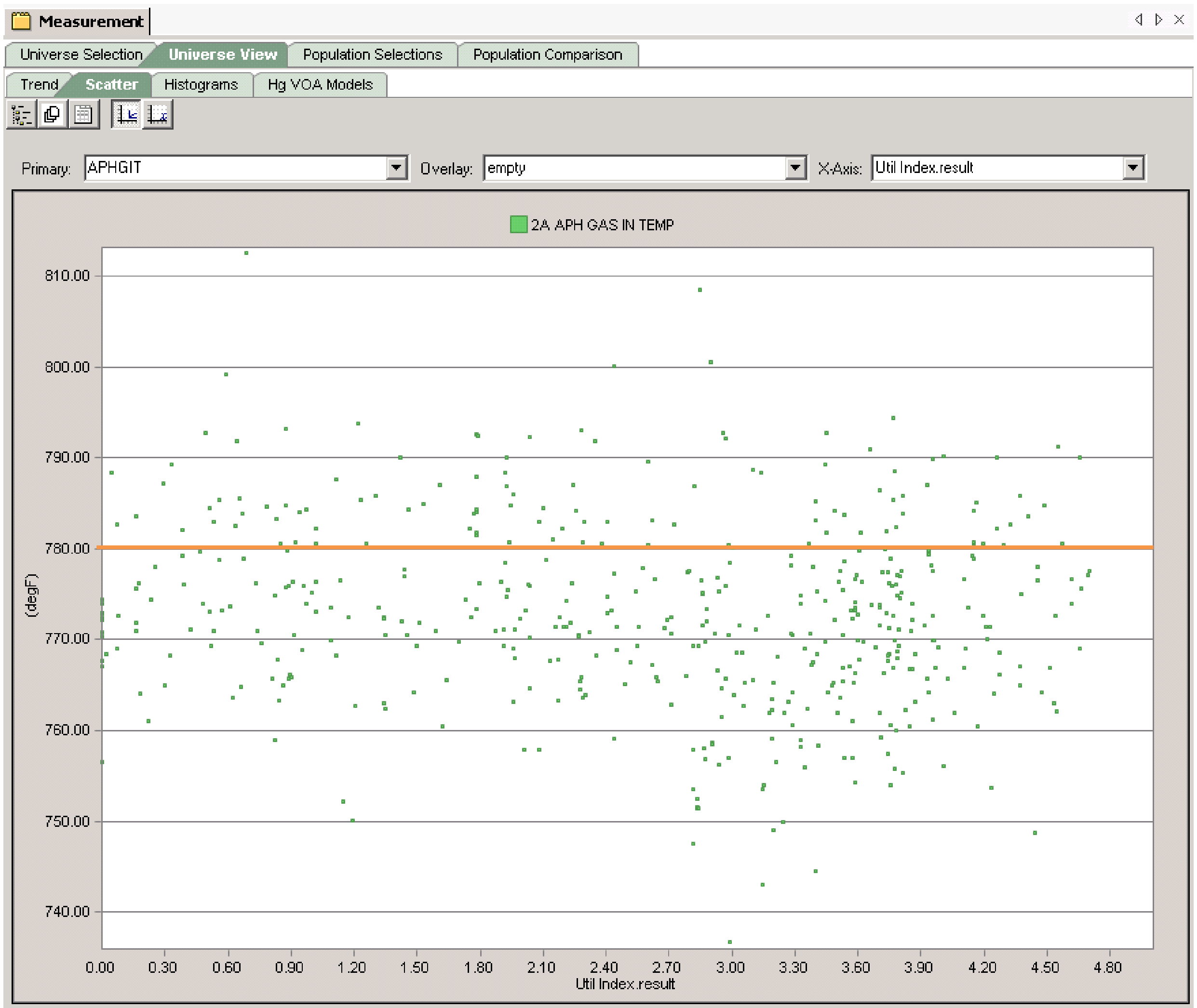

Figure 73: APHGIT A Side vs. Utilization

The trend for the B-side APH, which ran lower than the A, was more upward (if not flat), indicating that higher utilization was correlated with better balance and operation just below the objective limit.

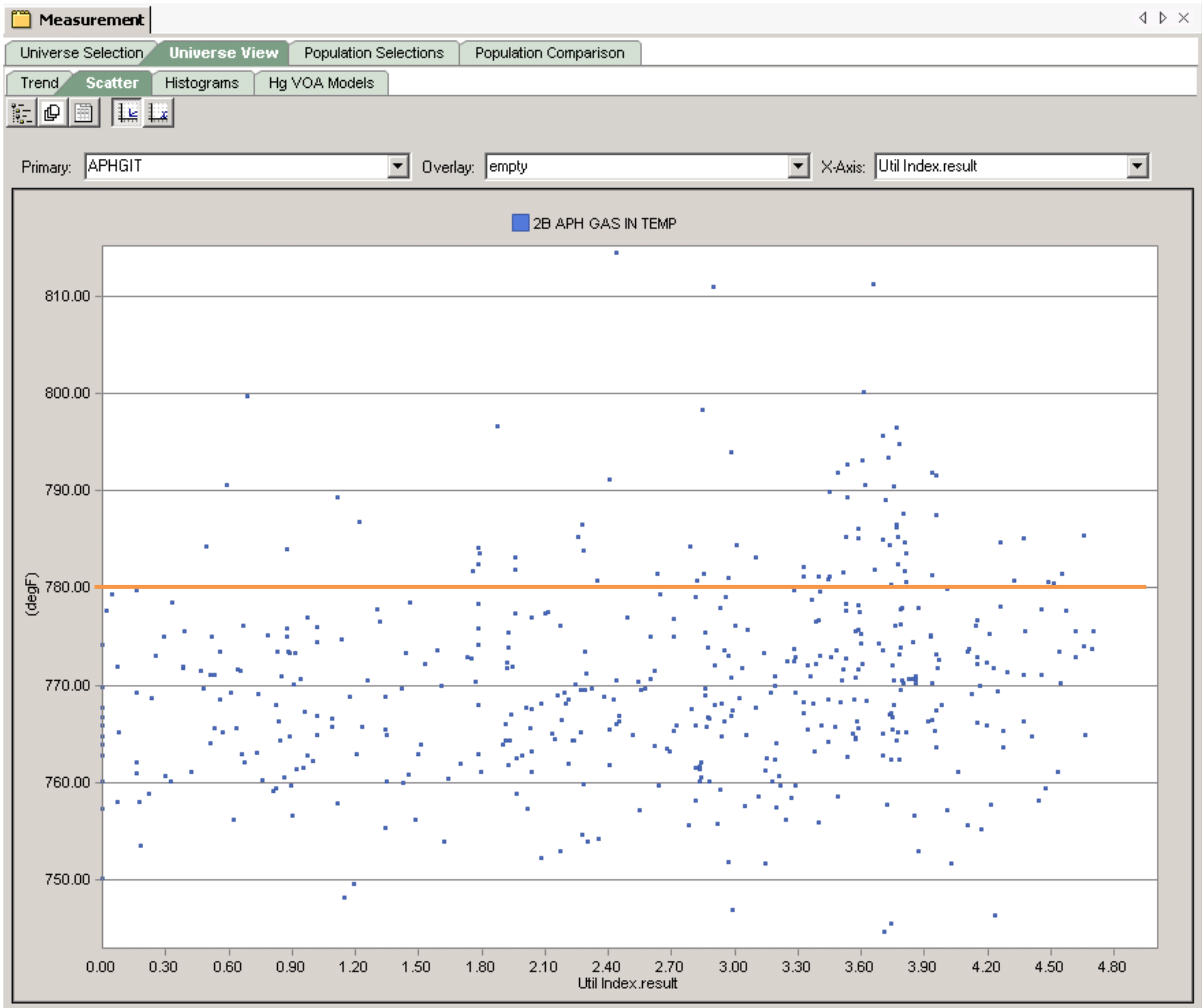

Figure 74: APHGIT B Side vs. Utilization Index

3.6.2.9 Long Term Trends, Observations

The following observations were made looking at the long term trends and correlations shown in Figure 50 - Figure 74.

The trends show the general movement over time of plant operation, at a given load, in the dimensions of fuel blend, Hg percent removal and total Hg production, NOx emission rate, CO emission rate, RH Temperatures and APH Gas Inlet Temperatures.

In short, Mercury production and NOx emissions were reduced, CO was held in check, RH Temps were sacrificed only to the degree desired, low O2 limits were obeyed, and improved behavior of back-end temperatures was achieved. Unfortunately, for the long time span examined in this section a reliable heat rate number does not exist.

3.6.3 Recent Trends and Correlations

The following section examines trends and correlations for more recent data. Data from 3/31/10 – 7/9/10 was filtered to select only samples where unit load was > 880MW. This section also looks at correlations between KPI's and utilization and introduces another index of utilization that captured the utilization of a wider set of optimization MV's.

3.6.3.1 Unit Load

Figure 75 shows the data from the analysis period 3/31/10 – 7/9/10 filtered for unit load greater than 880 MW, and Figure 76 shows that when above 880 MW, the majority of time was spent between 900 and 905 MW.

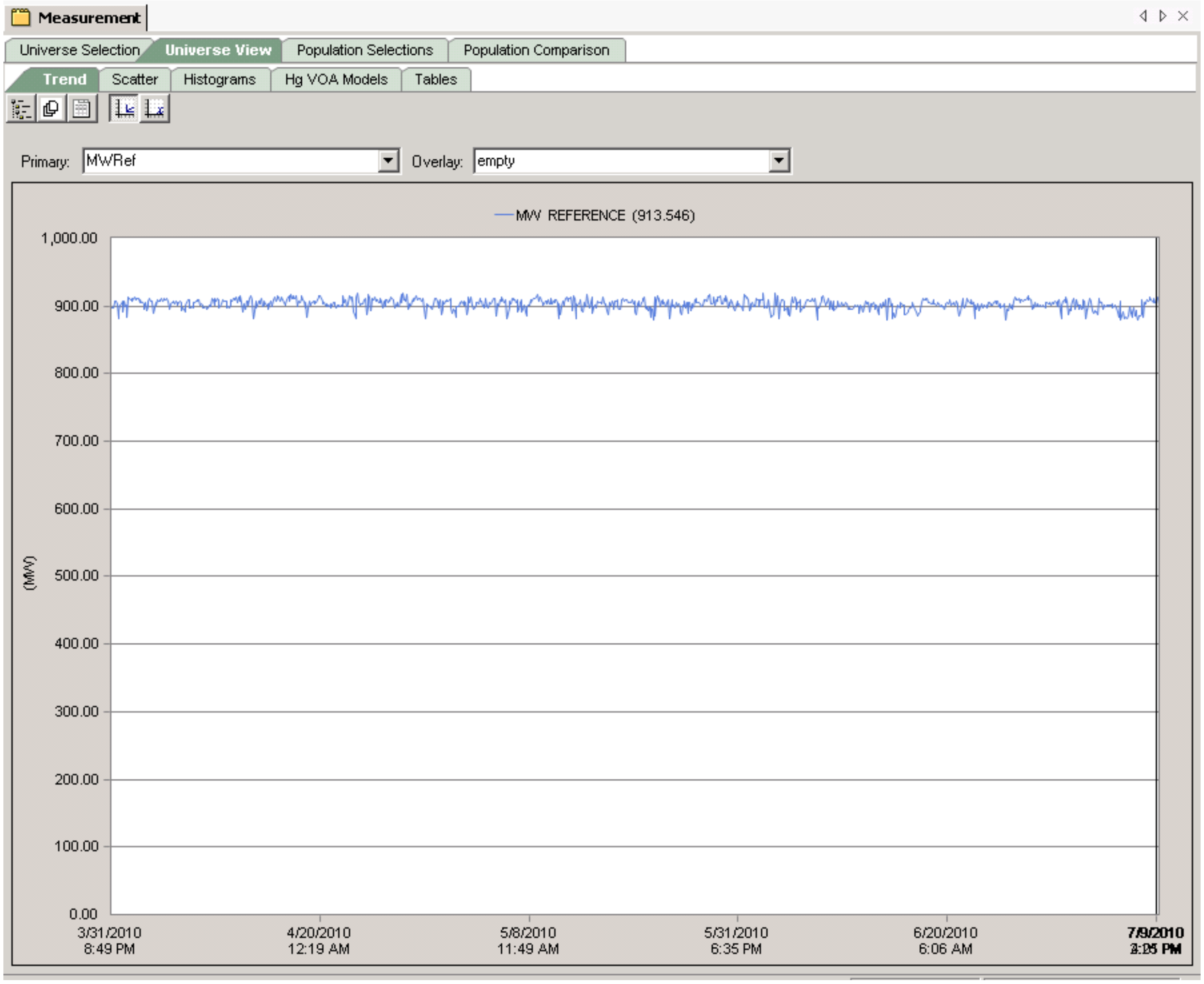

Figure 75: Data where MW>880, 3/3/10-7/09/10

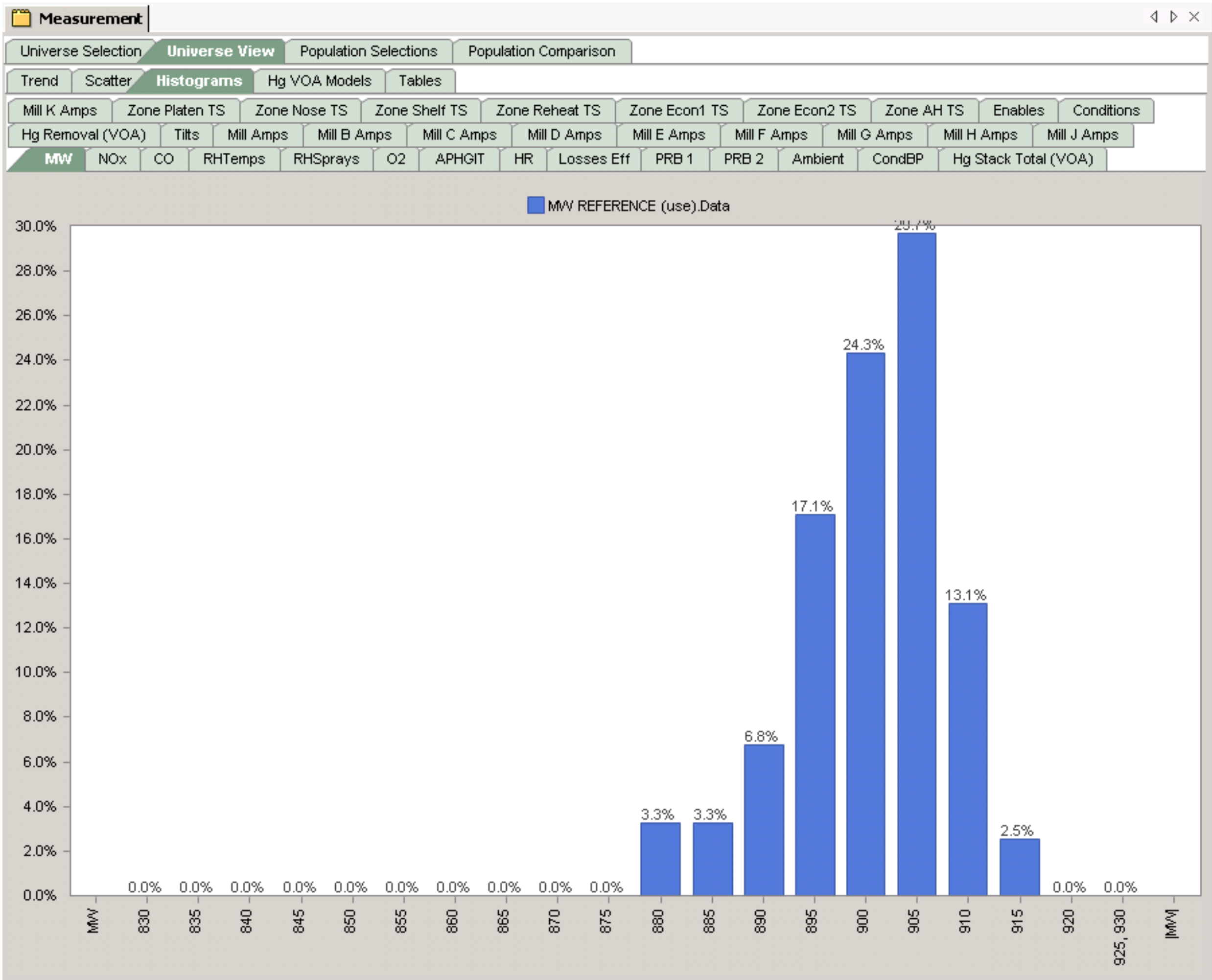

Figure 76: MW distribution when MW >880

3.6.3.2 PRB Blend

Figure 77 shows the trend of PRB blend along with two utilization indices (red and green lines).

Figure 77: PCT PRB and utilization indices, where MW>880, 3/31/10-7/9/10

Figure 78 shows PRB blend plotted vs. utilization. Lignite fuel has higher Nitrogen content than PRB fuel. If an inverse relationship existed (blend trending down with increasing utilization), it would indicate that periods of higher utilization coincide with periods of lower PRB percentage, which would bias NOx higher. “Util Index” is an index that captures the degree to which the largest levers on stoichiometry and heat transfer are enabled. It looks at SootOpt ON, CombustionOpt ON, O2Trim MV ON, and Burner Tilt MV ON. On means enabled for optimization.

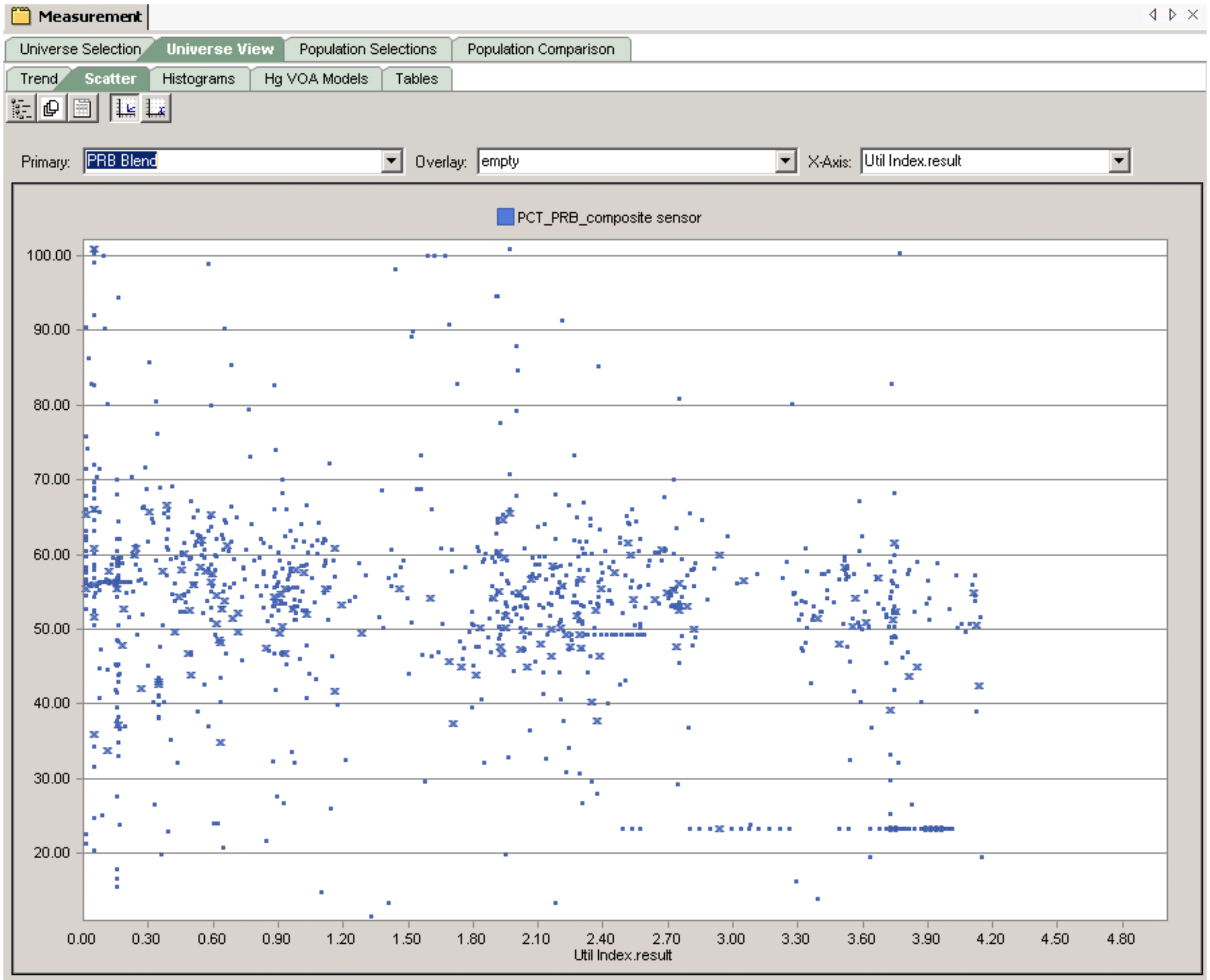

Figure 78: PCT PRB vs. Utilization Index

“Util Index(23)” – the Broader Utilization Index shown in Figure 79 - gauged the degree to which the wider set of combustion optimization MV’s are enabled in addition to the major enables. Higher values in Figure 79 mean higher utilization.

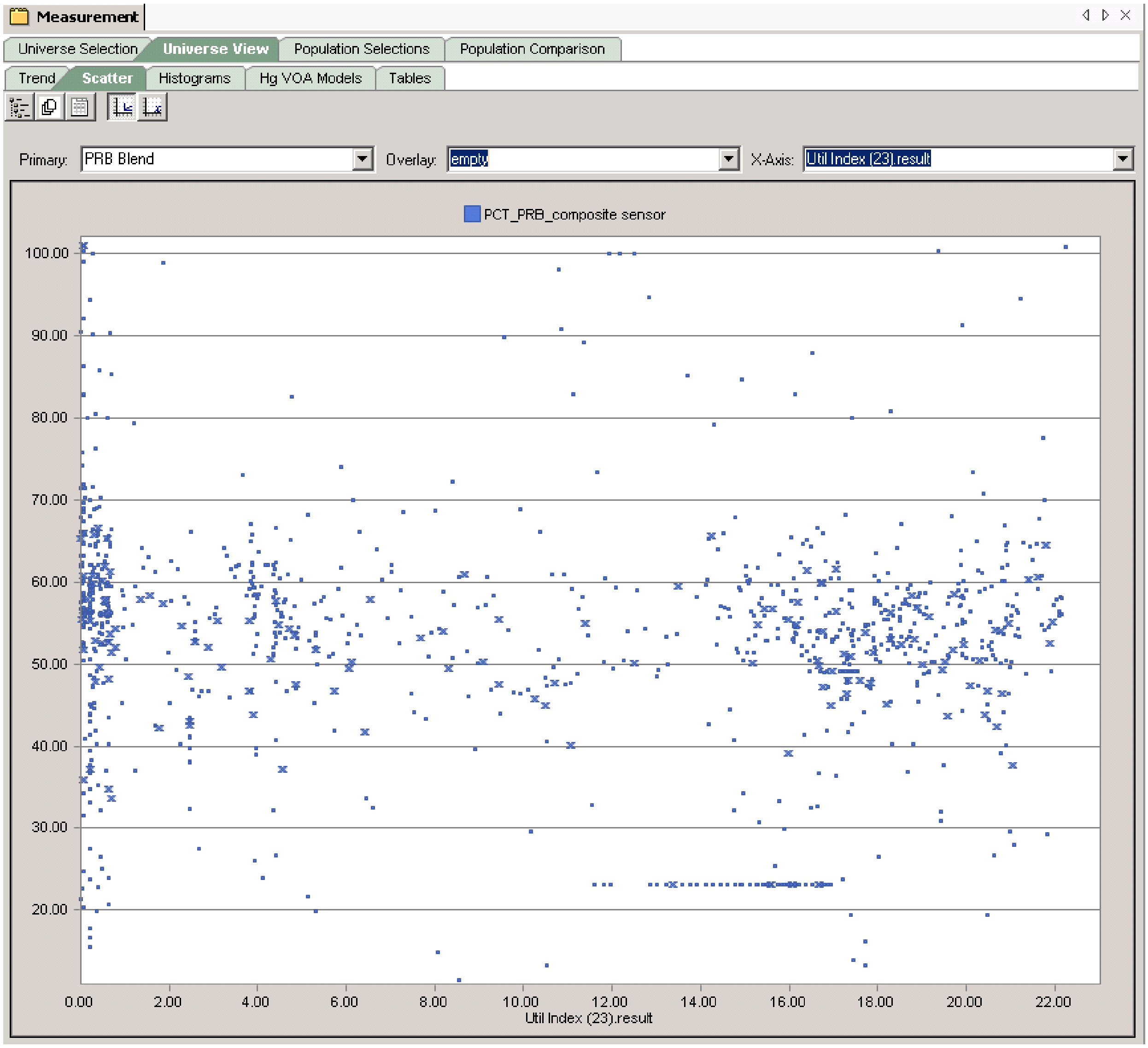

Figure 79: PCT PRB vs. Broader Utilization Index (Util Index(23))

3.6.3.3 Mercury Removal (VOA)

Figure 80 shows the Mercury Removal (VOA) prediction along with the two indices of utilization (blue and orange lines). Note: no outlier was seen. This shows that the model was not calibrated in a way that accounts for fuel blend.

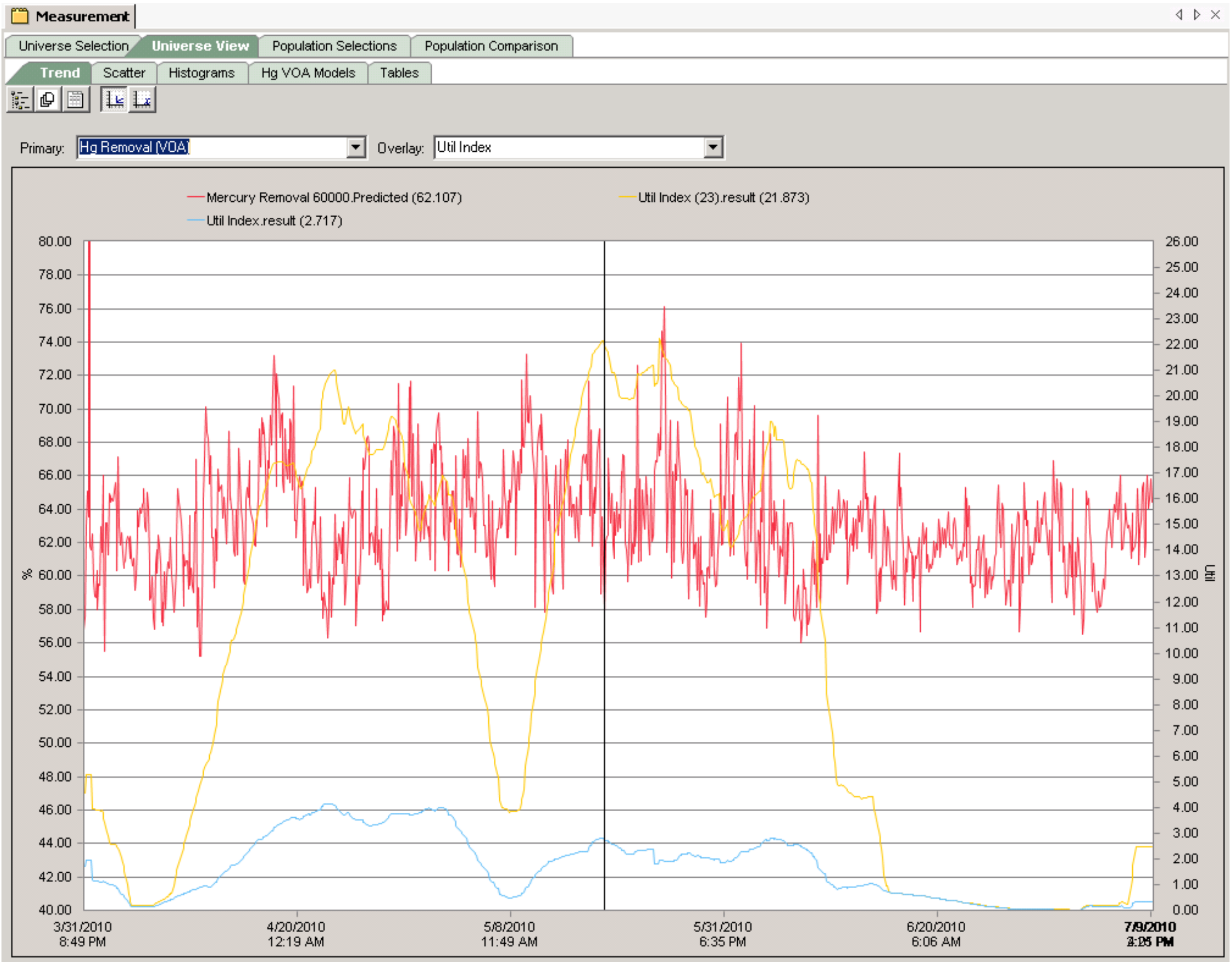

Figure 80: VOA Predicted Hg Removal and Utilization Indices

Figure 81 shows the Mercury Removal VOA prediction vs. "Util Index". The upward trend with increasing utilization means that a positive effect on Mercury Removal was seen with increasing utilization.

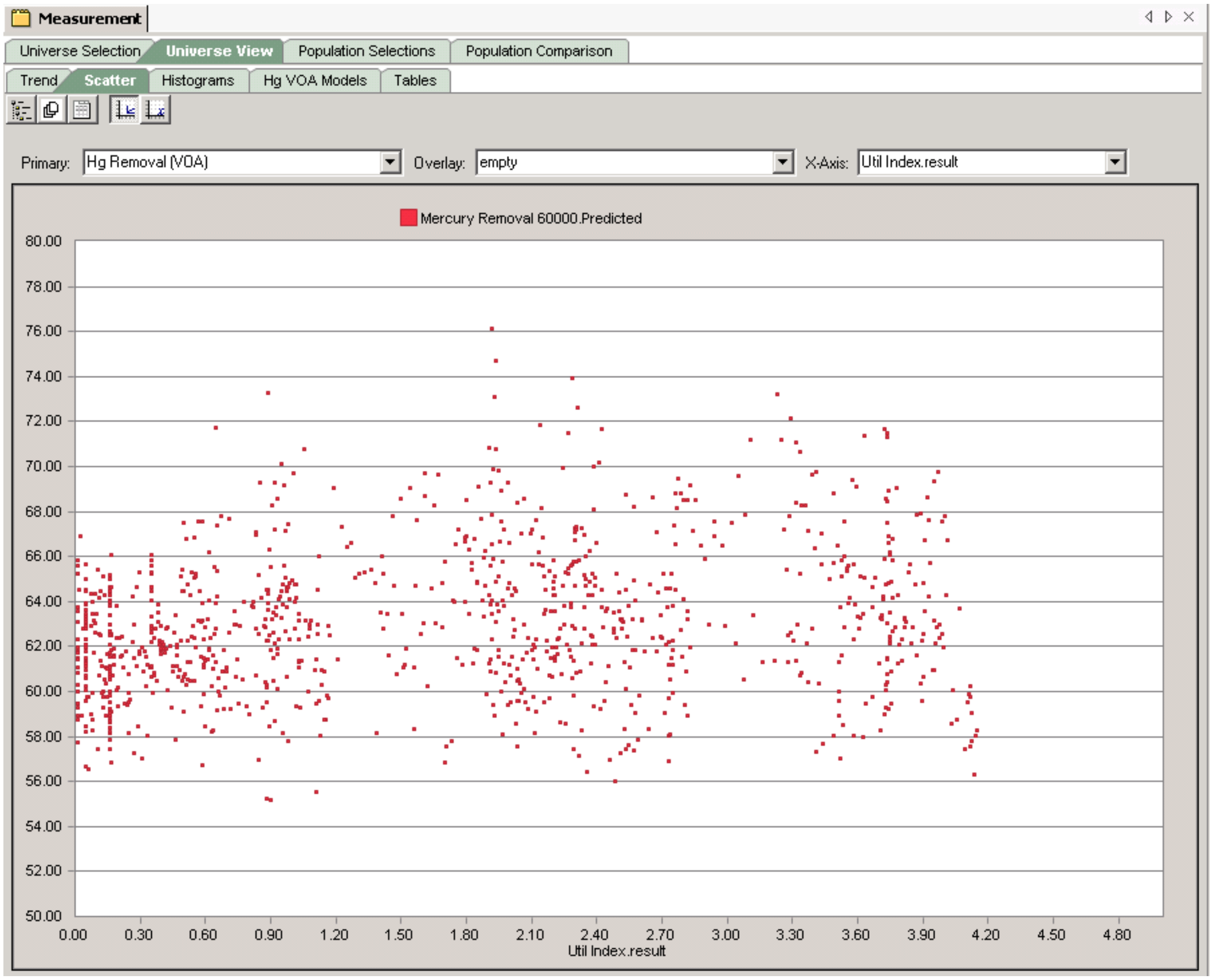

Figure 81: Hg Removal vs. Util Index

Figure 82 shows the Mercury Removal VOA prediction vs. "Util Index(23)". The upward trend with increasing utilization means that a positive effect on Mercury Removal was seen with increasing utilization.

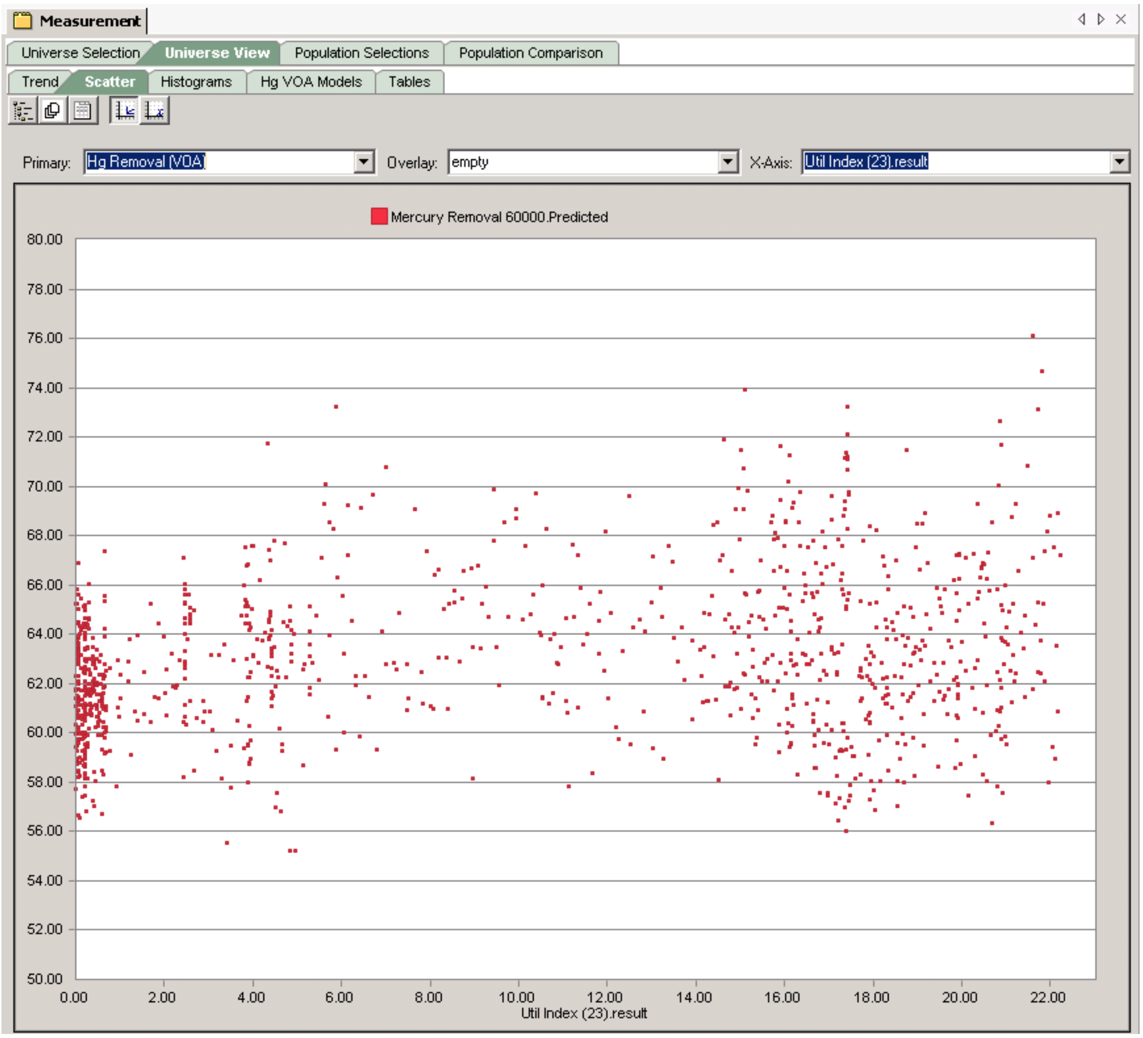

Figure 82: Hg Removal VOA Prediction vs. Broader Utilization Index (Util Index(23))

3.6.3.4 Mercury Stack Total (VOA)

Figure 83 shows the Mercury Stack total model (VOA) prediction along with the two indices of utilization. Note the outlier region where PRB blending did not occur. This shows how the model was calibrated to respond strongly to the behavior of the blend signal.

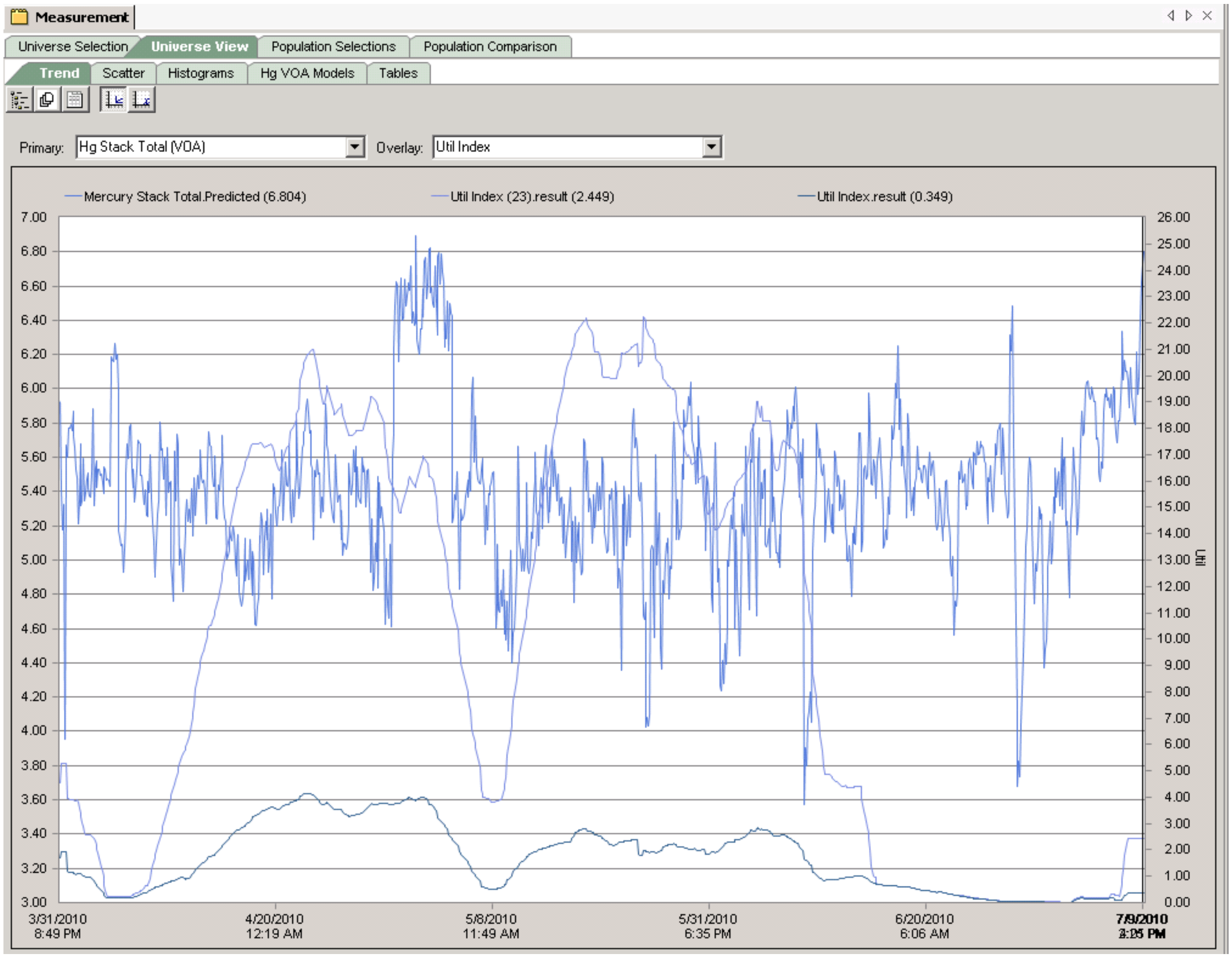

Figure 83: VOA Predicted Hg Stack Total and Utilization Indices

Figure 84 shows the Mercury Stack Total VOA prediction vs. "Util Index". The downward trend in Mercury stack total with increasing utilization means that an inverse effect was seen on Mercury with increasing utilization. Given that no positive relationship was seen between utilization and blend in the Demonstration project, this would suggest that non-fuel related optimization did have an effect on Mercury production. Note the outlier cluster at (3.60, 6.4). This cluster corresponds to the period where no blending was done.

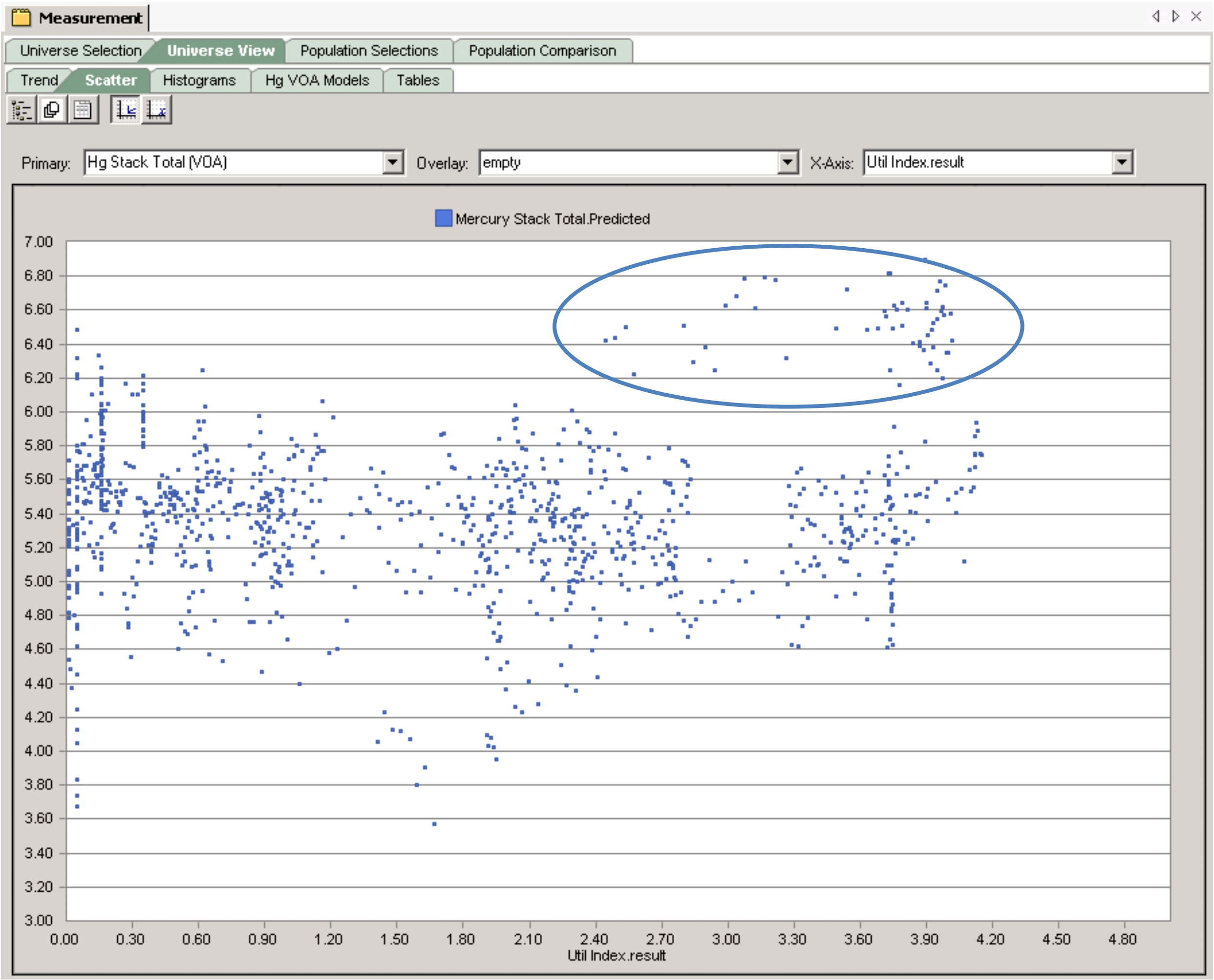

Figure 84: VOA Predicted Mercury Stack Total vs. Utilization Index

Figure 85 shows VOA predicted Mercury Stack Total vs. the broader index of utilization ("Util Index(23)"). The outlier cluster can be seen at the top.

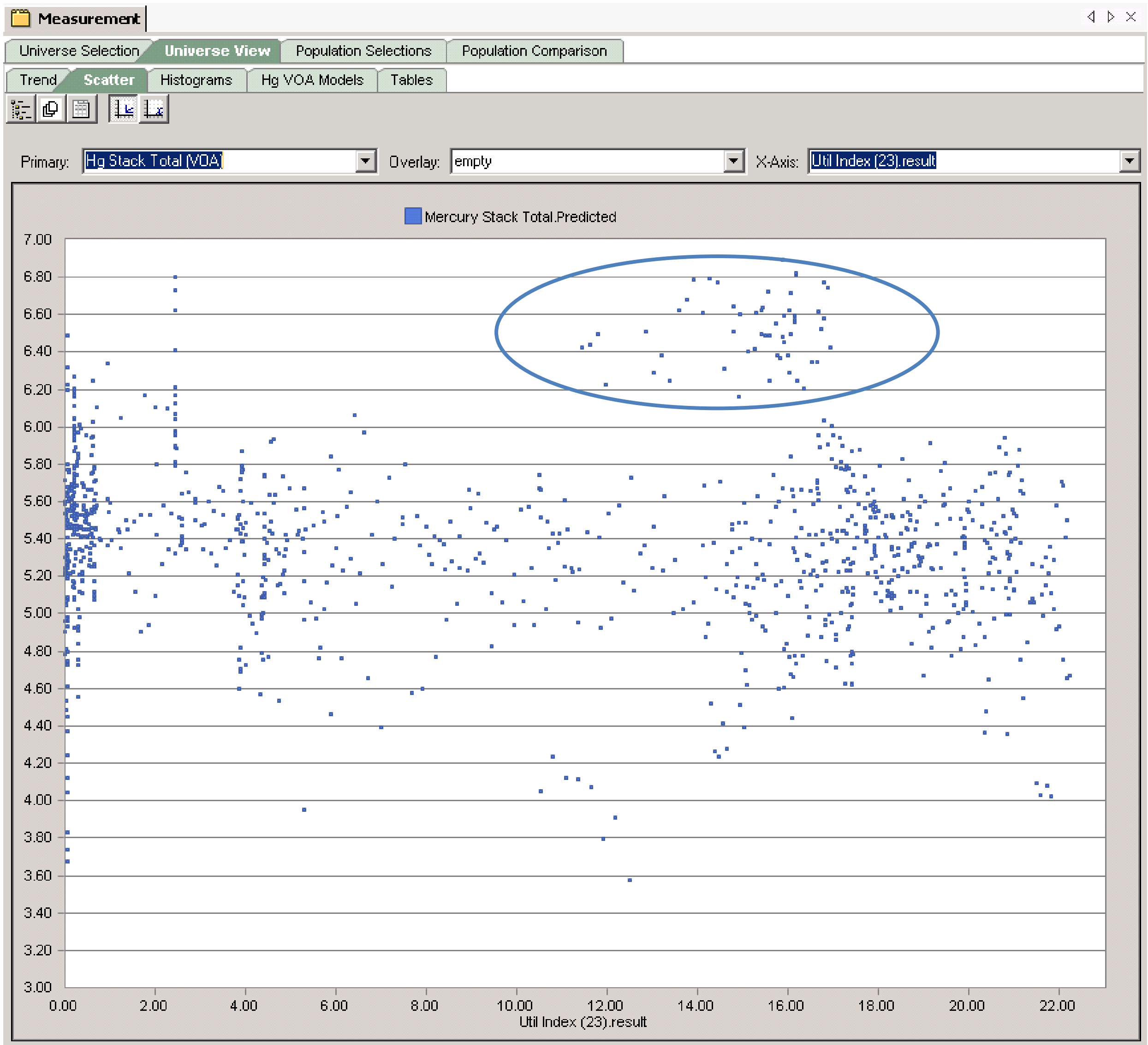

Figure 85: Mercury Stack Total vs. Broader Utilization Index(Util Index(23))

3.6.3.5 CEMS NOx

Figure 86 shows CEMS NOx and the two utilization indices in red and green respectively.

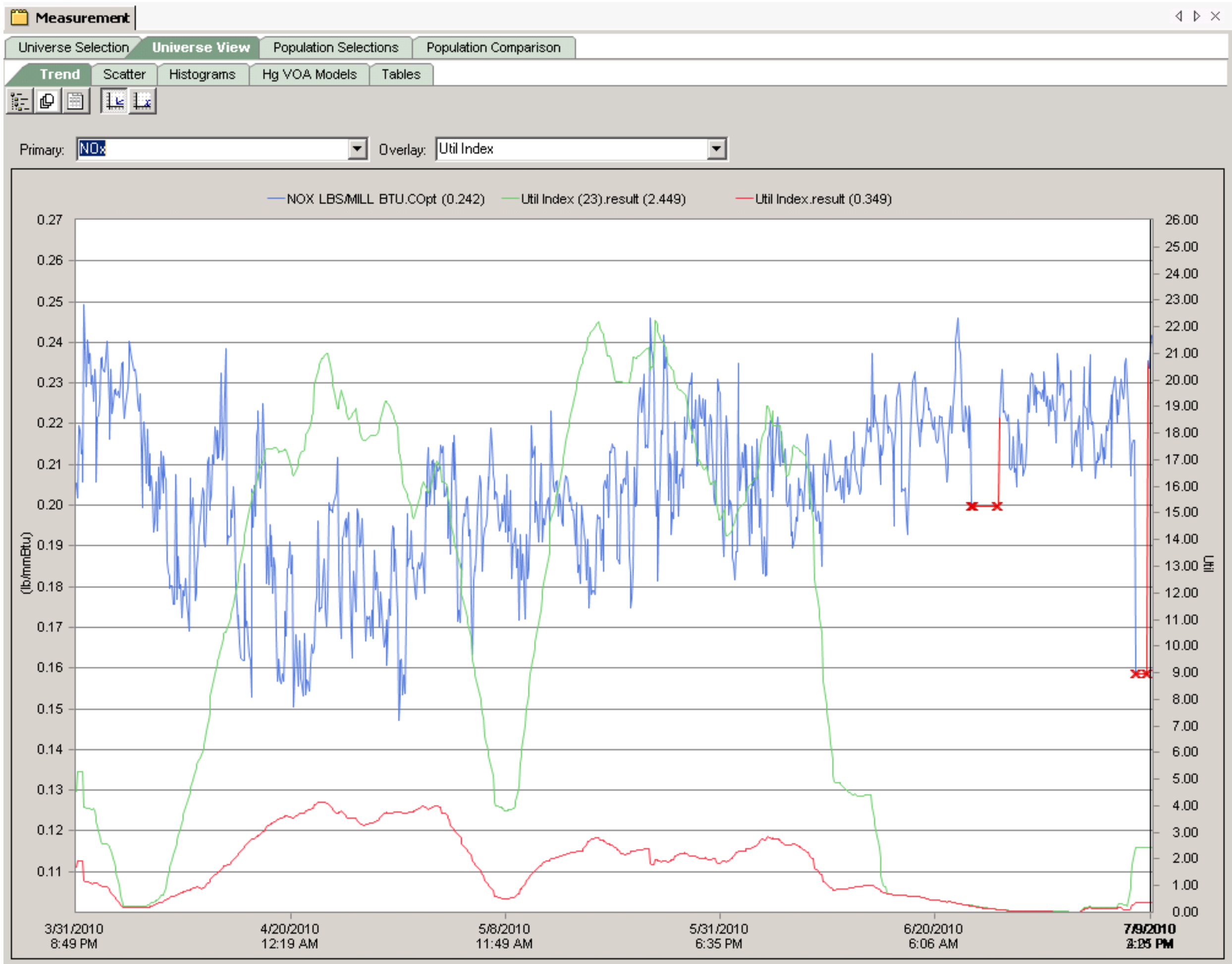

Figure 86: CEMS NOx and Utilization Indices

In Figure 87 the downward trend in NOx with increasing utilization means that an inverse effect was seen with increasing utilization. Given than no positive relationship was seen between utilization and blend, this would suggest that non-fuel related optimization did have an effect on NOx production.

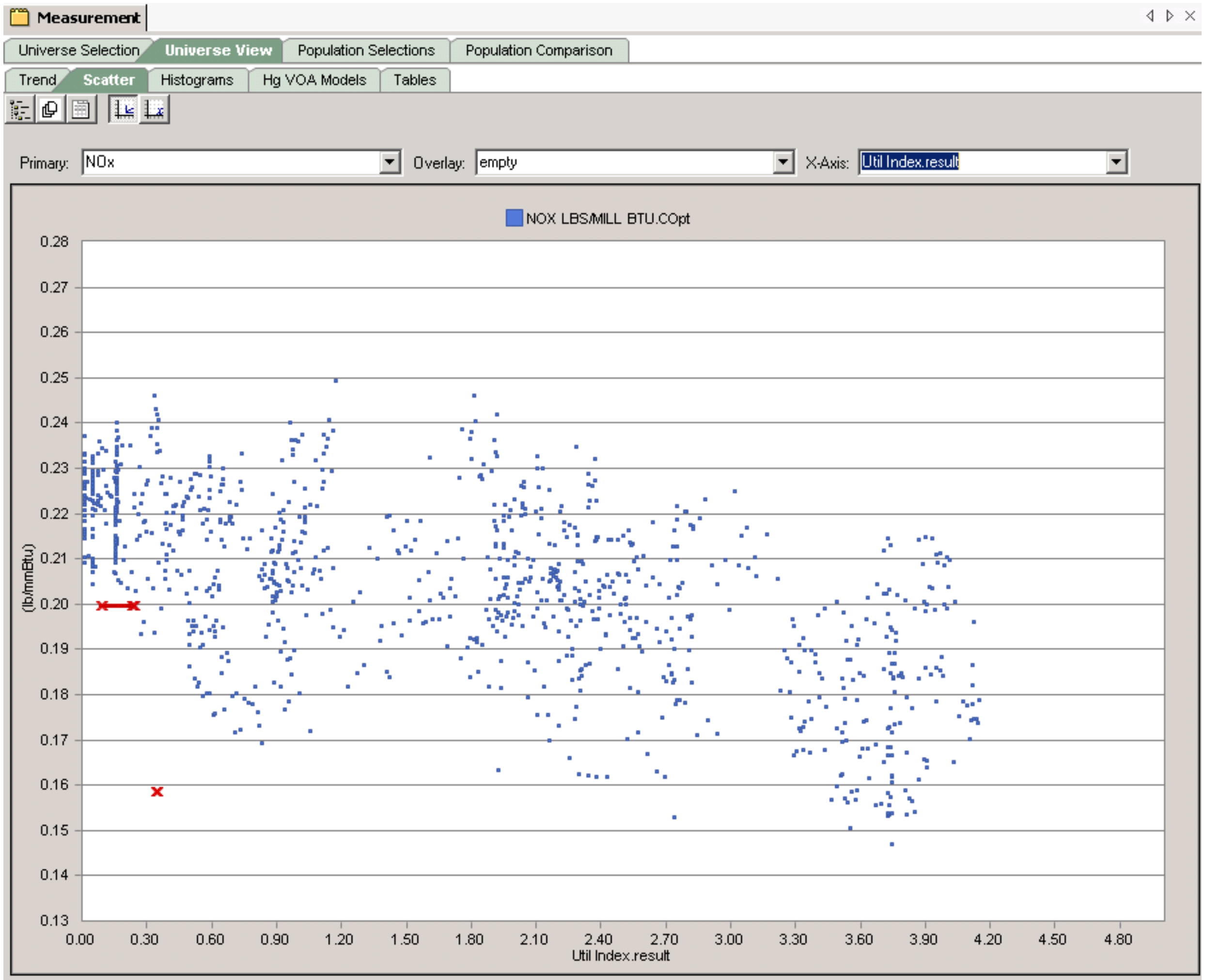

Figure 87: CEMS NOx vs. Utilization Index

Figure 88 shows CEMS NOx plotted vs. Util Index (23). The downward trend with increasing utilization suggests that utilization had an inverse effect on NOx.

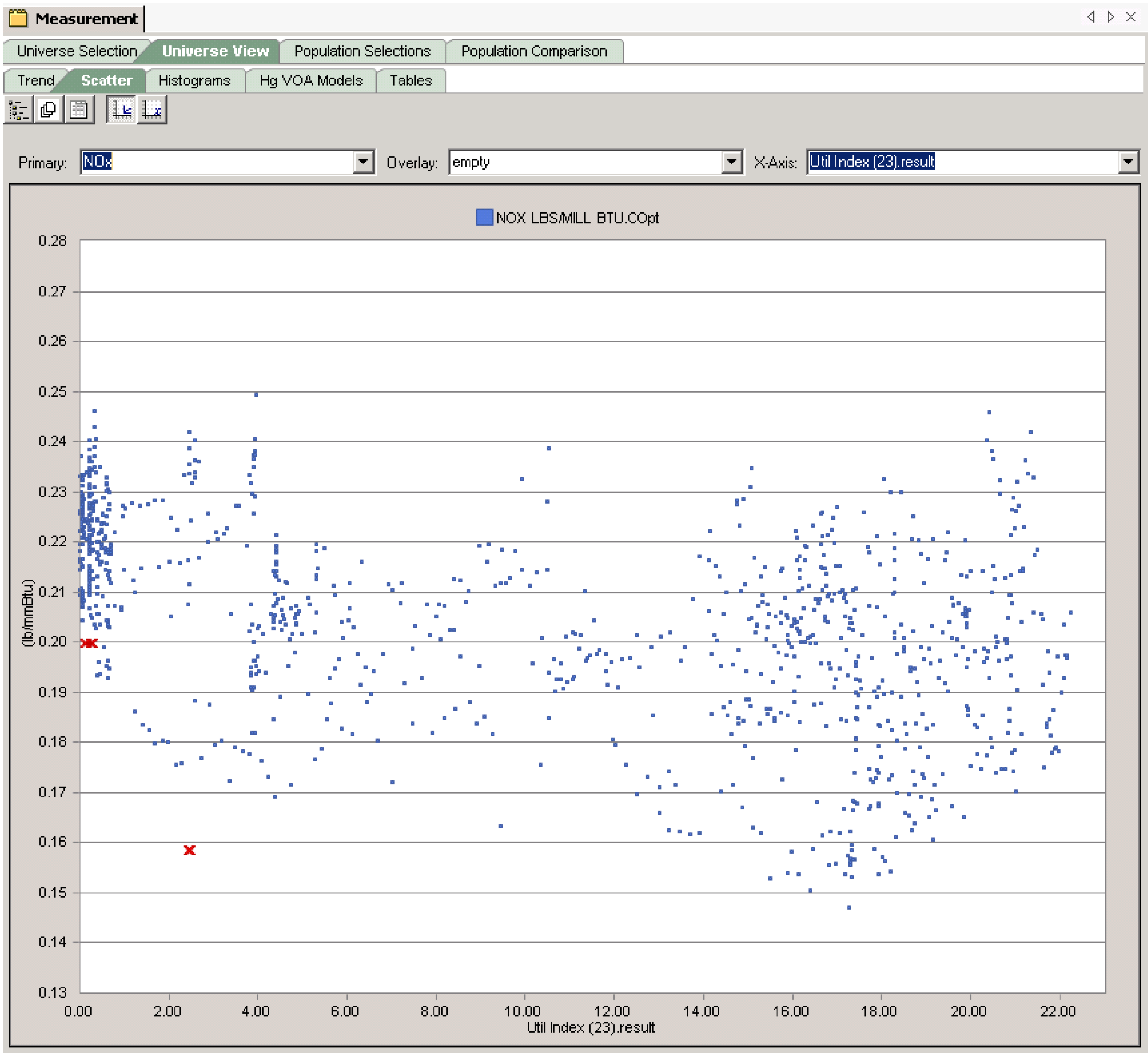

Figure 88: CEMS NOx vs. Broader Utilization Index (Util Index(23))

3.6.3.6 CEMS CO

Figure 89 shows CEMS Stack CO plotted with indices of utilization (green and red lines). The objective was to keep CO under 40ppm (recently changed to 30ppm).

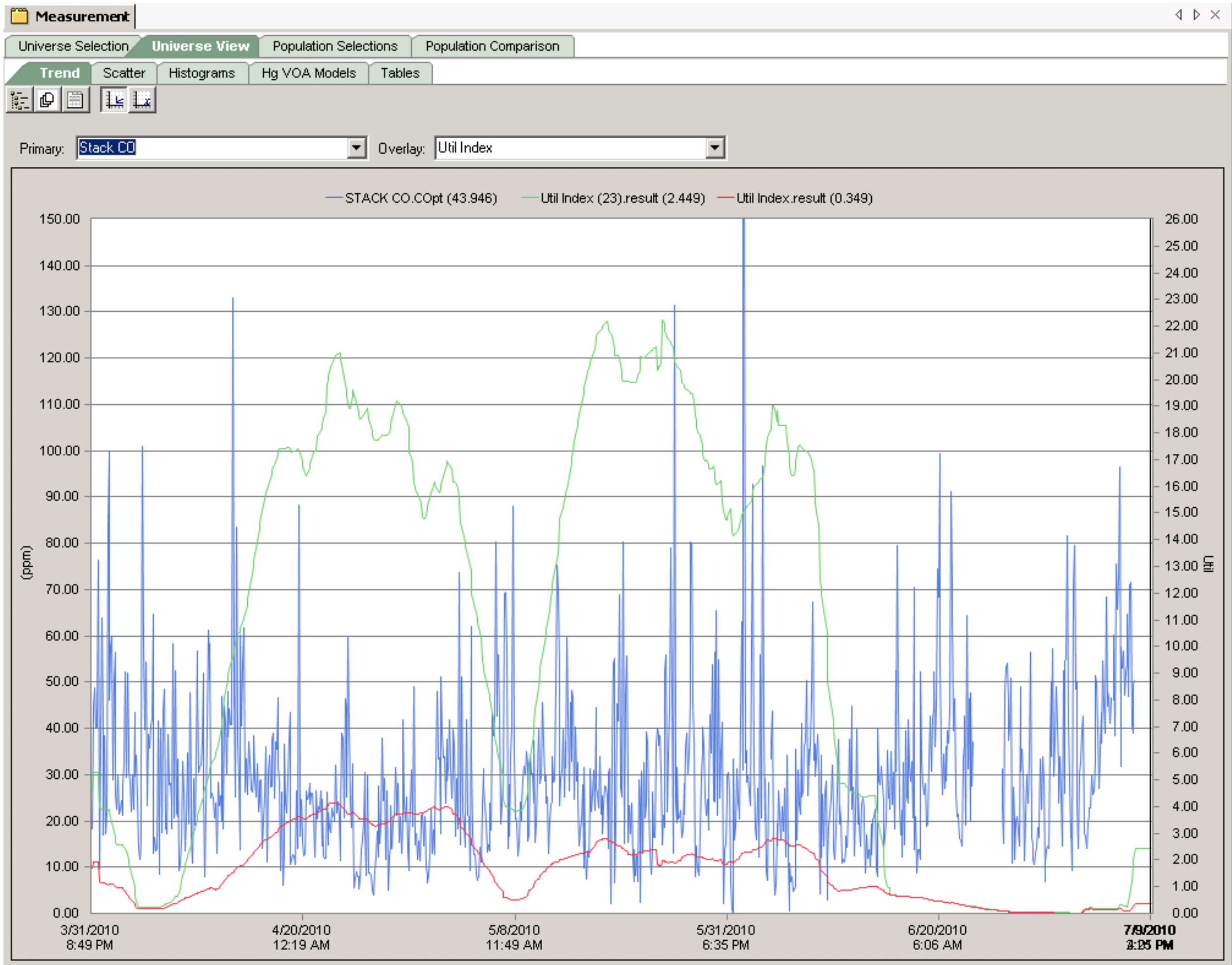

Figure 89: CEMS CO and Utilization Indices

Figure 90 shows CEMS CO plotted vs. Util Index. The objective was to keep CO below 40ppm (recently changed to 30ppm). The downward trend with increasing utilization suggests that utilization had an inverse effect on CO.

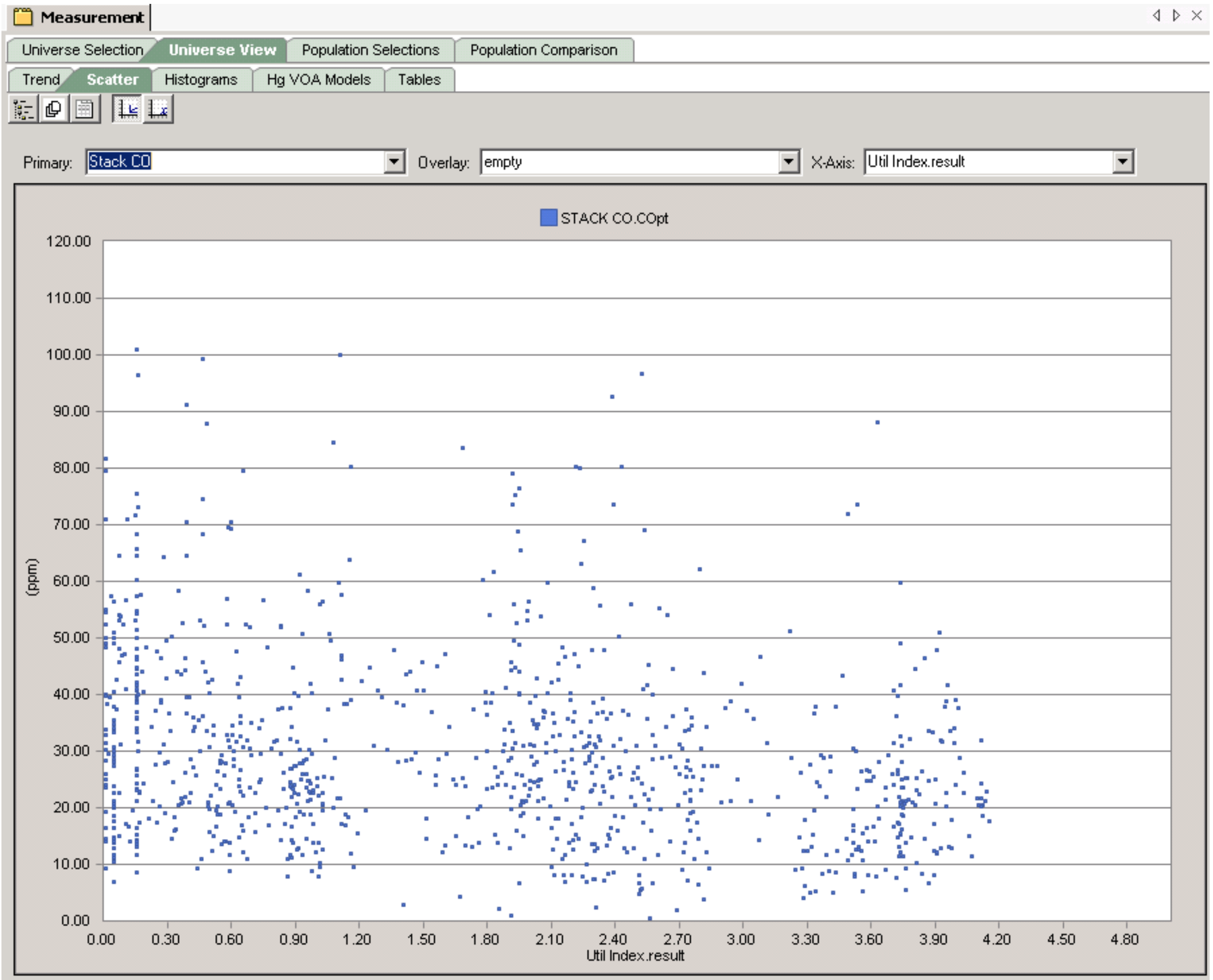

Figure 90: CEMS CO vs. Utilization Index

Figure 91 shows CEMS CO plotted vs. Util Index(23). The objective was to keep CO below 40ppm (recently changed to 30ppm). The downward trend with increasing utilization suggests that utilization had an inverse effect on CO.

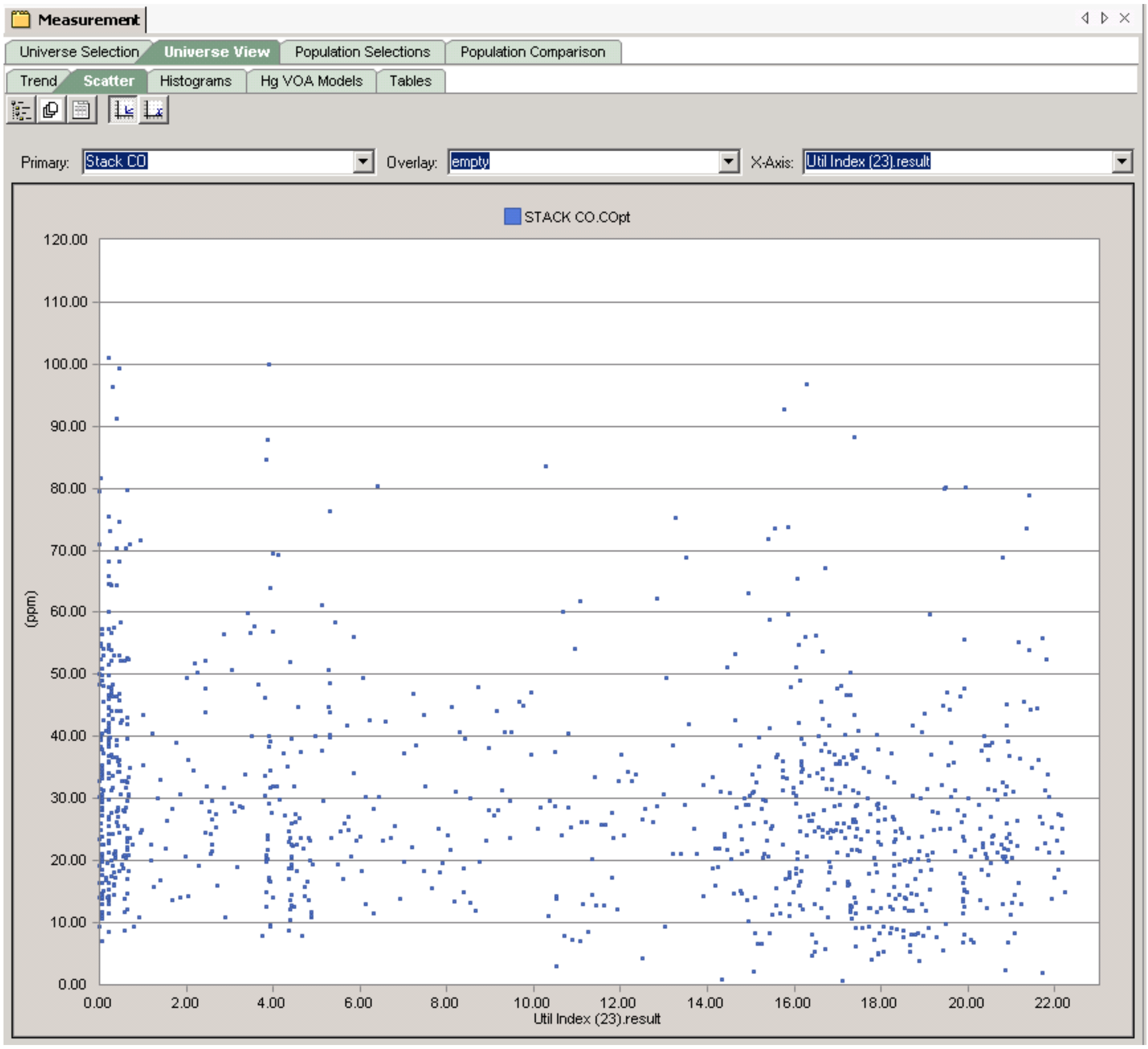

Figure 91: CEMS CO vs. Broader Utilization Index (Util Index(23))

3.6.3.7 RH Temps

Figure 92 shows A and B side RH Temps plotted with indices of utilization. The objective was to keep RH Temp above 980 degF.

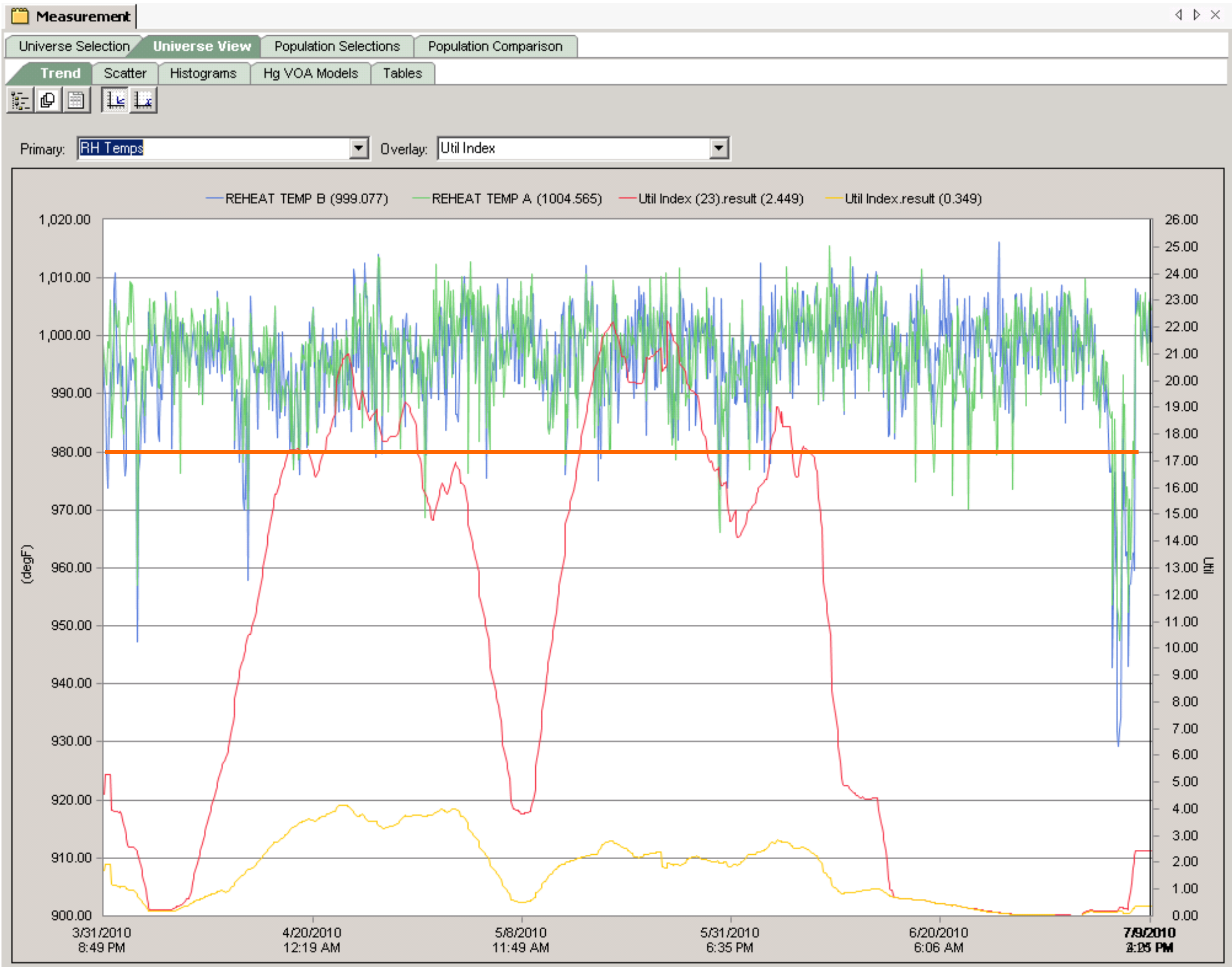

Figure 92: RH Temp A and B with Indices of Utilization

Figure 93 shows A and B side RH Temps plotted vs. Util Index. The objective was to keep Temps above 980 degF. The downward trend with increasing utilization suggests that utilization had an inverse effect on RH Temps.

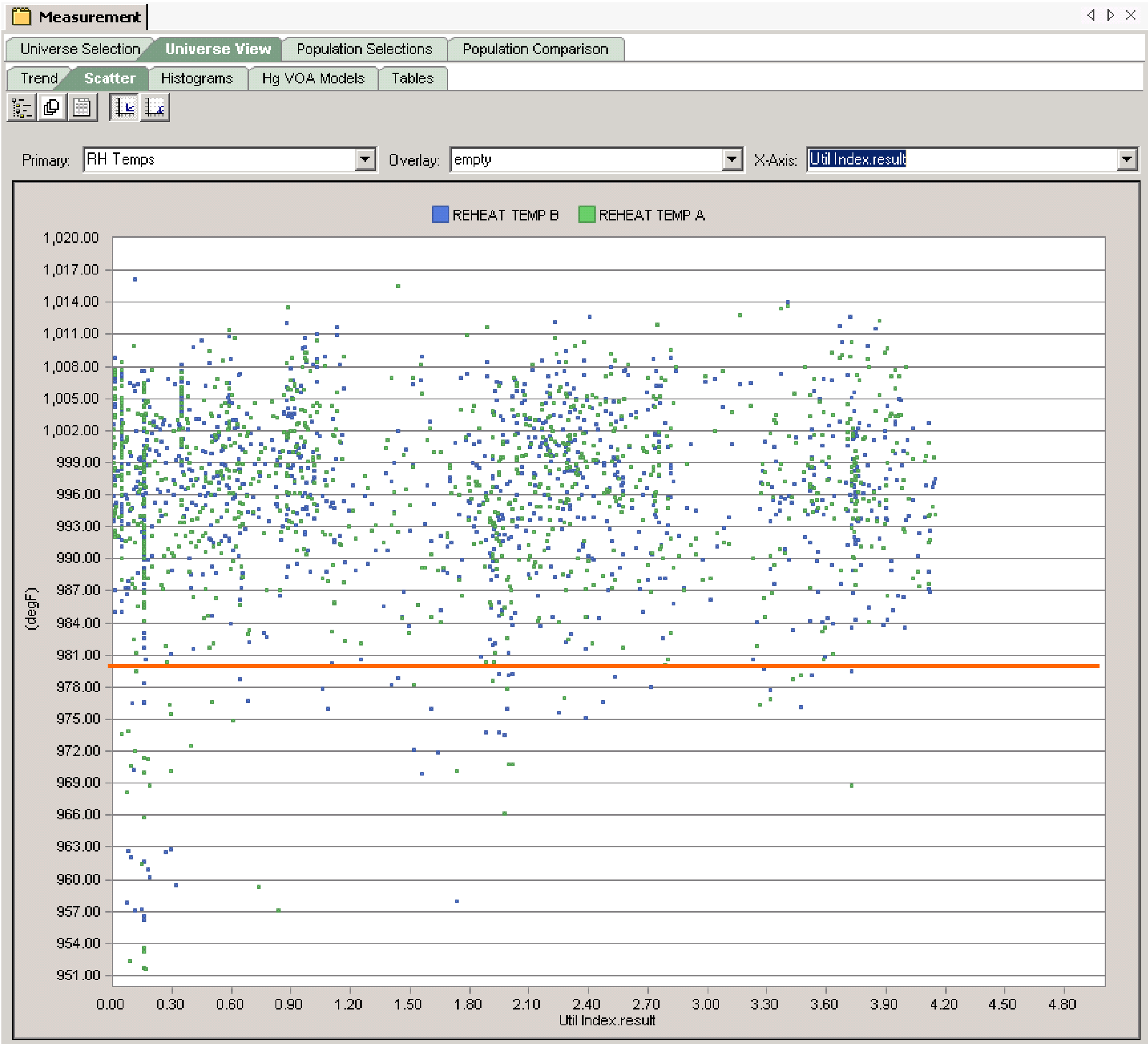

Figure 93: RH Temps A and B vs. Utilization Index

Figure 94 shows A and B side RH Temps plotted vs. Util Index. The objective was to keep Temps > 980 degF. The downward trend with increasing utilization suggests that utilization had an inverse effect on RH Temps.

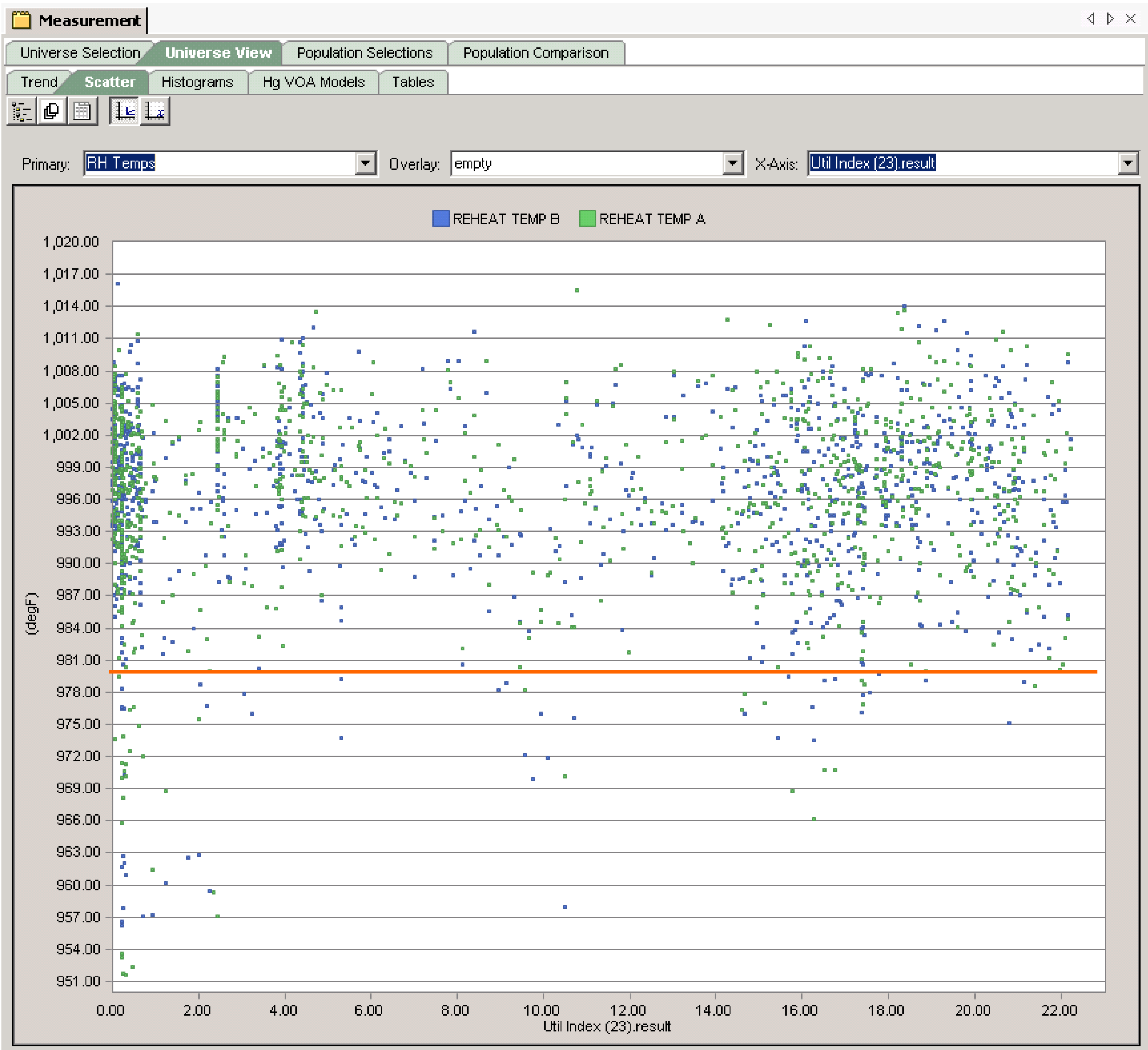

Figure 94: A and B Side RH Temps vs. Broader Utilization Index (Util Index (23))

3.6.3.8 Average Boiler O2

Figure 95 shows average Boiler O2 plotted with indices of utilization. The objective was to keep O2 above 2 %.

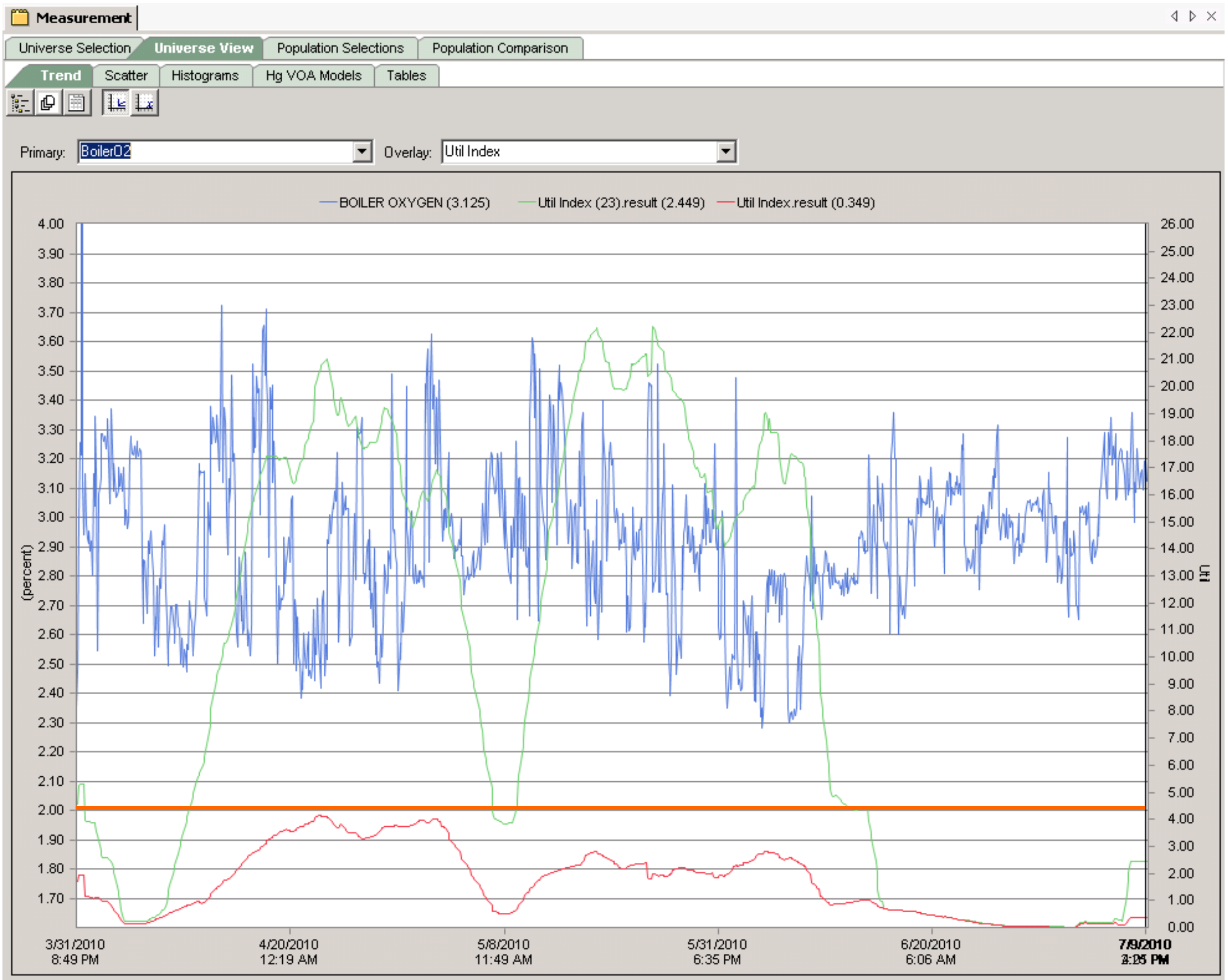

Figure 95: Average Boiler O2 (blue) with Indices of Utilization

Figure 96 shows average Boiler O2 plotted vs. Util Index. The objective was to keep O2 above 2 %.

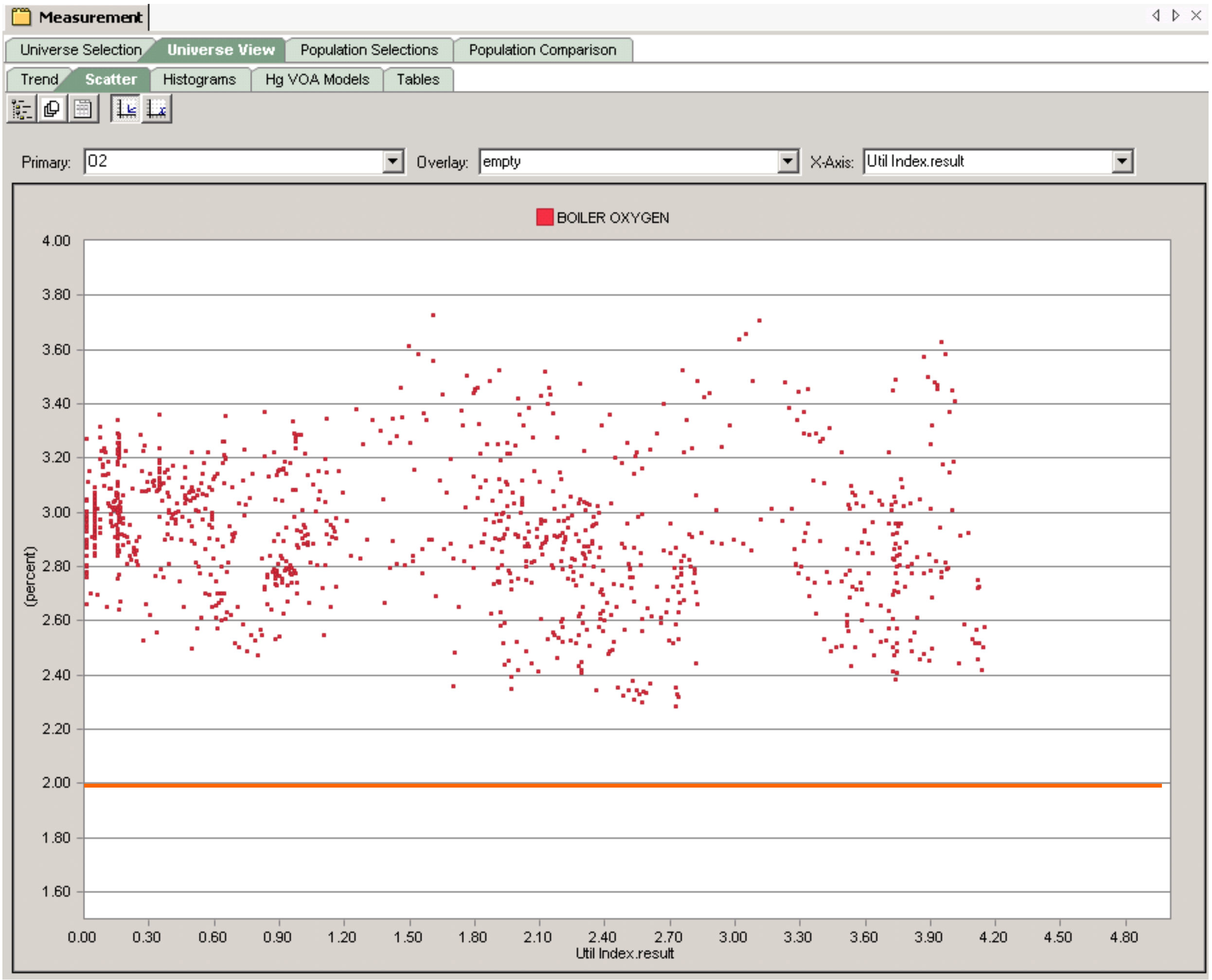

Figure 96: Average Boiler O2 vs. Utilization Index

Figure 97 shows average Boiler O2 plotted vs. Util Index(23). The objective was to keep O2 above 2 %.

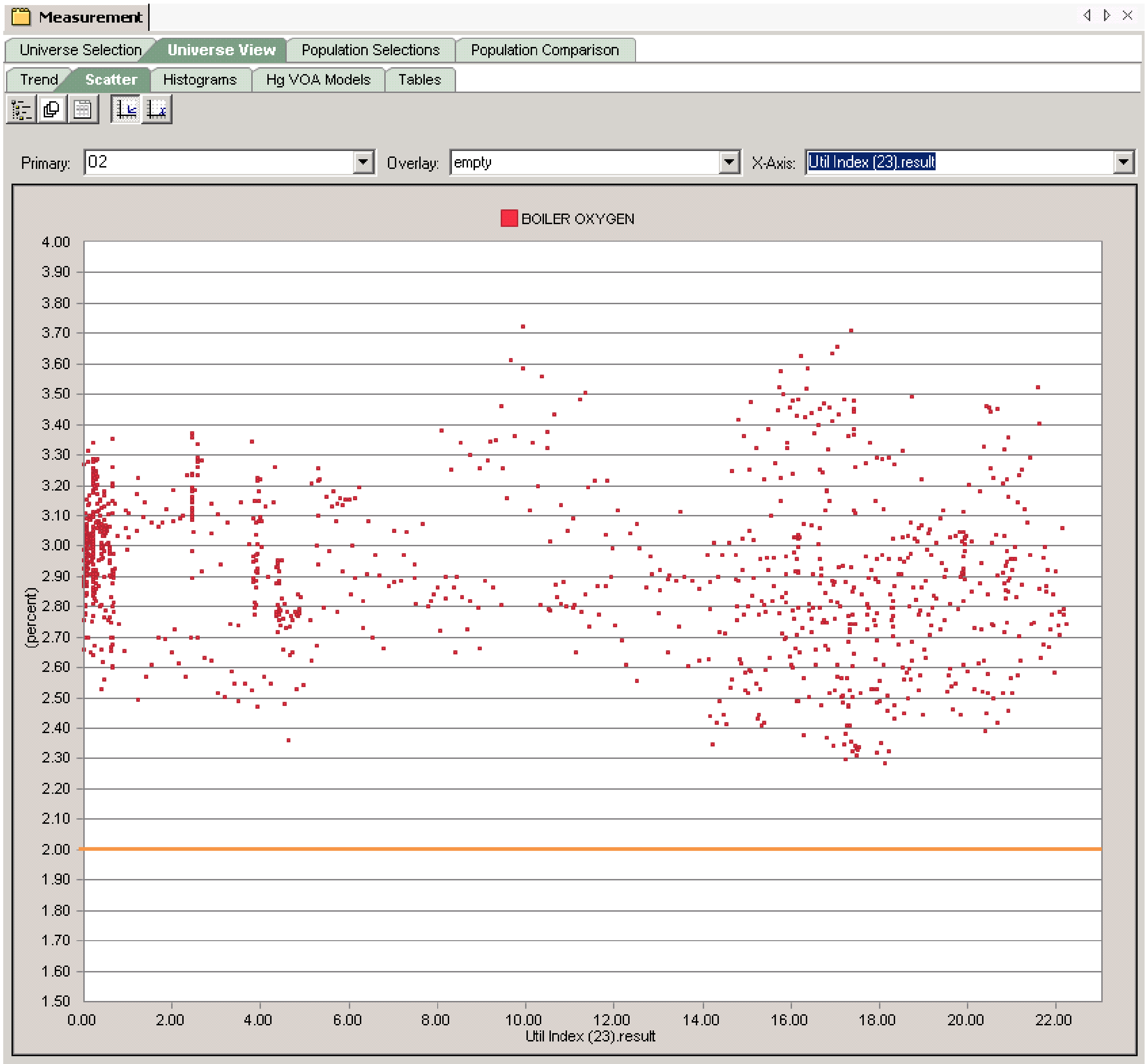

Figure 97: Average Boiler O2 vs. Broader Utilization Index (Util Index (23))

3.6.3.9 A and B Side O2

Figure 98 shows A and B Side O2 plotted with indices of utilization. The objective was to keep O2 above 2 %.

Figure 98: A (blue) and B (green) Side O2 with Utilization Indices

Figure 99 shows average A and B side Boiler O2 plotted vs. Util Index. The objective was to keep O2 above 2 %.

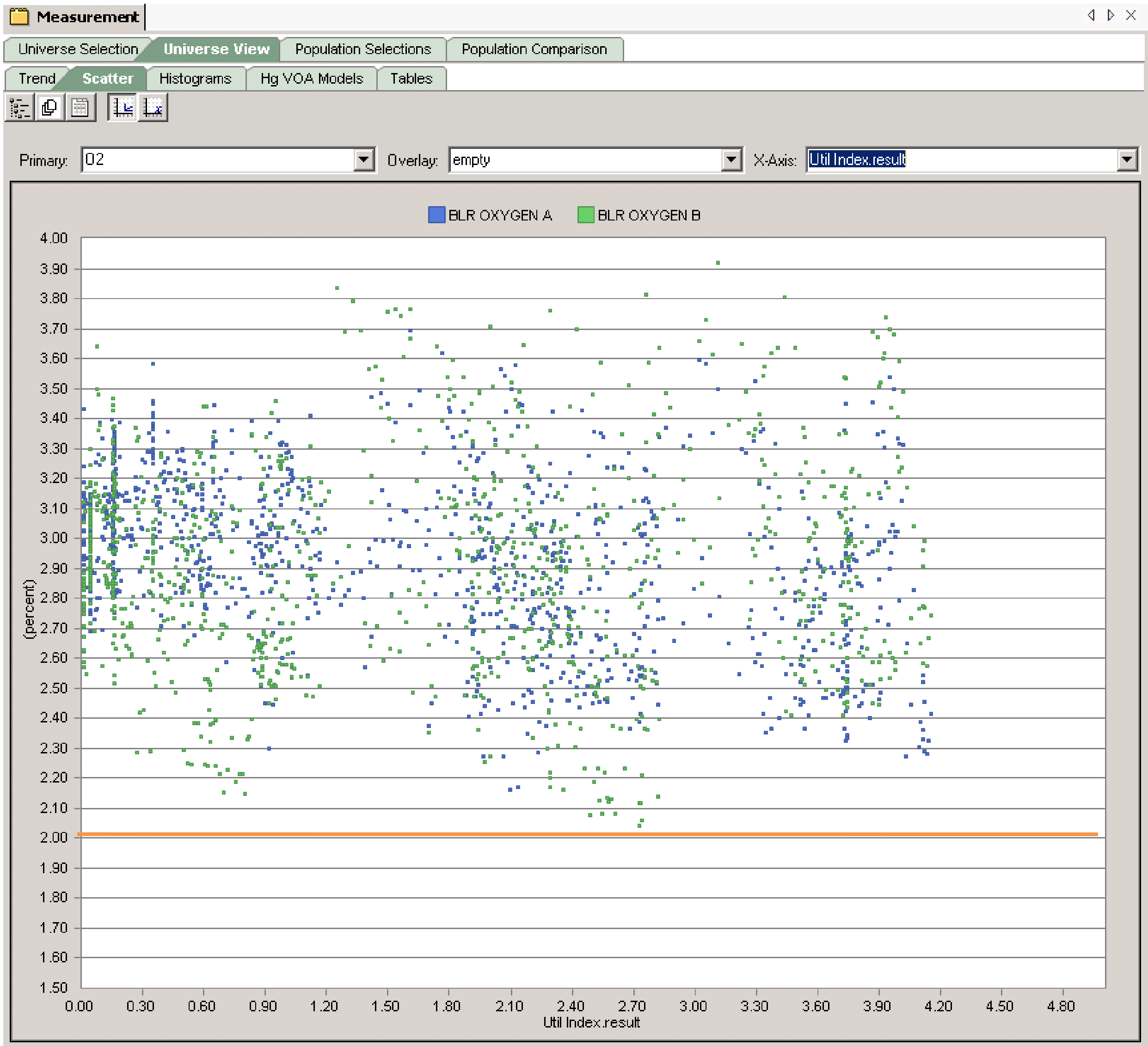

Figure 99: A (blue) and B (green) Side O2 vs. Utilization Index.

Figure 100 shows average A and B side Boiler O2 plotted vs. Util Index(23). The objective was to keep O2 above 2 %.

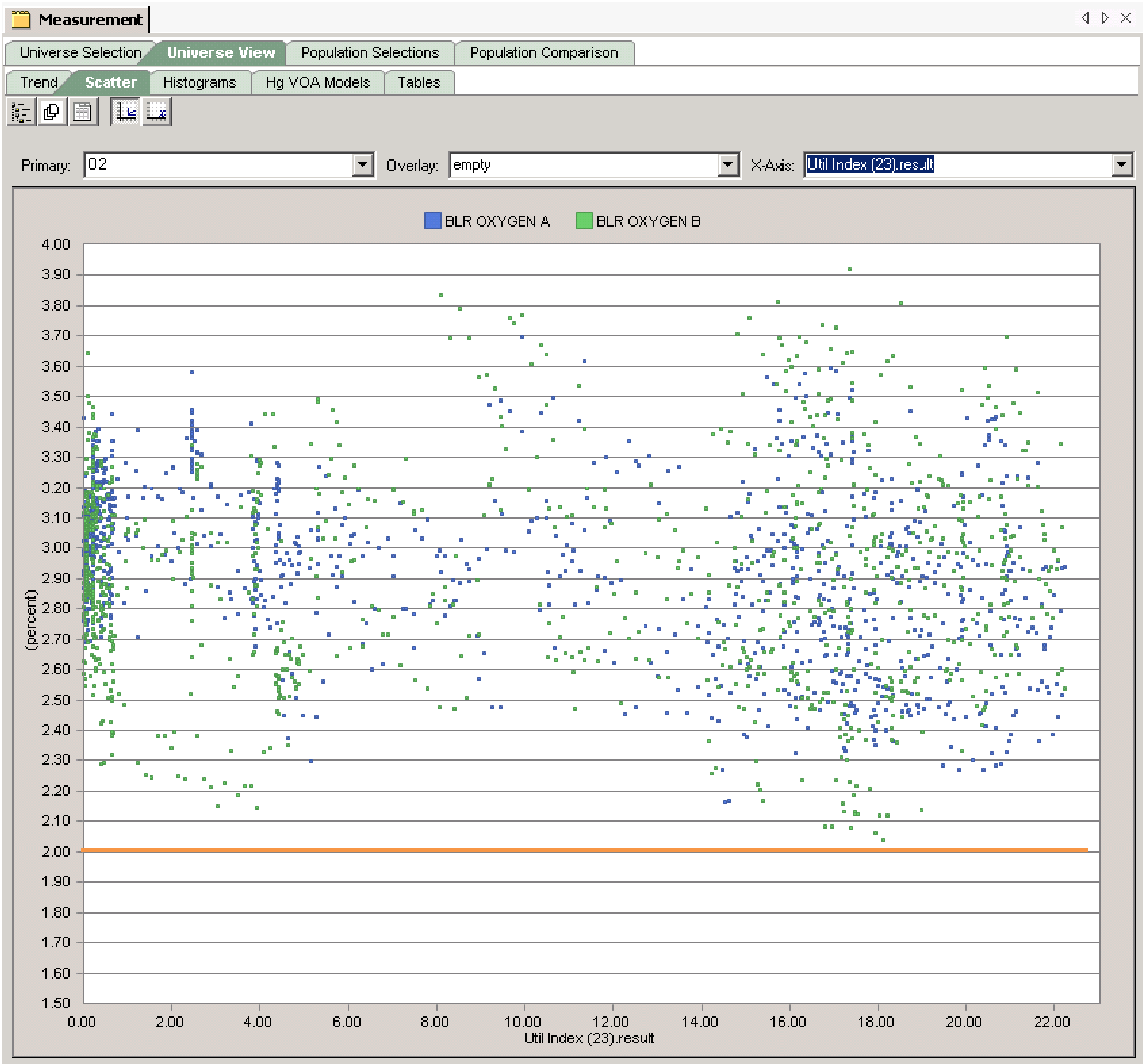

Figure 100: A (blue) and B (green) side O2 vs. Broader Utilization Index (Util Index(23)).

3.6.3.10 Net Unit Heat Rate

Figure 101 shows PerformanceOpt's Net Unit Heat Rate plotted with indices of utilization.

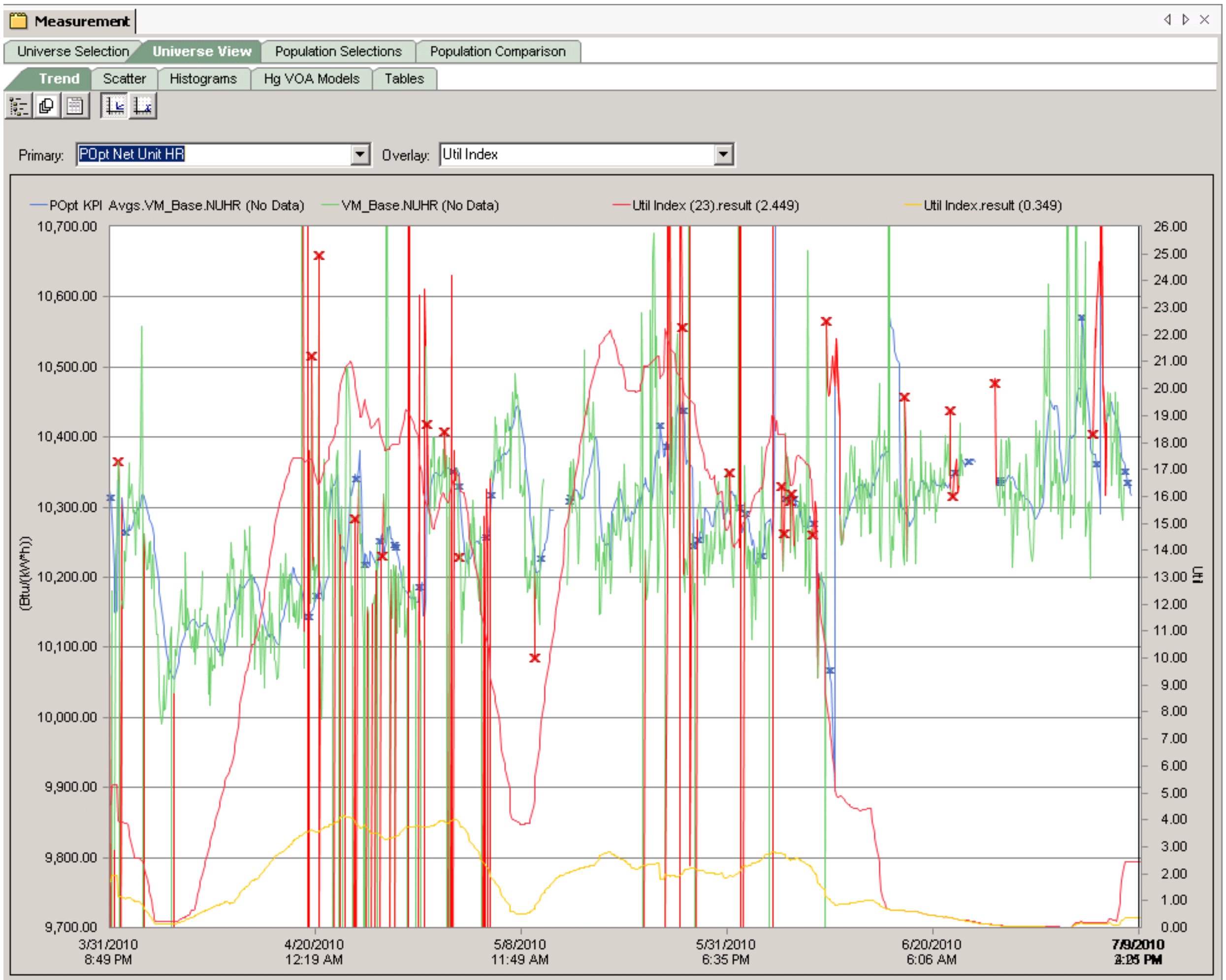

Figure 101: PerformanceOpt Net Unit Heat Rate with Indices of Utilization

Figure 102 shows PerformanceOpt's Net Unit Heat Rate plotted vs. Util Index.

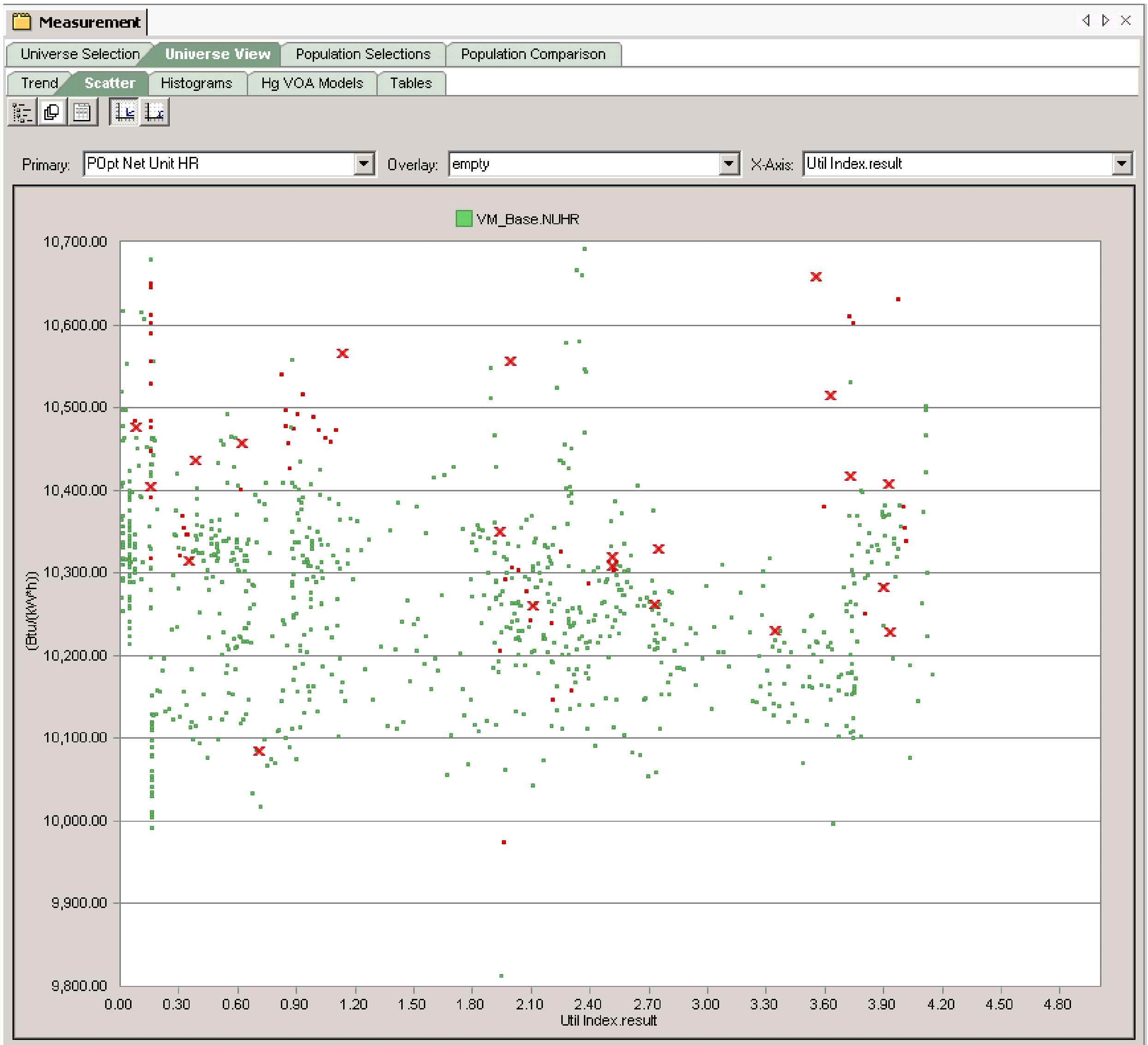

Figure 102: PerformanceOpt Net Unit Heat Rate vs. Utilization Index

Figure 103 shows PerformanceOpt's Net Unit Heat Rate plotted vs. Util Index(23)

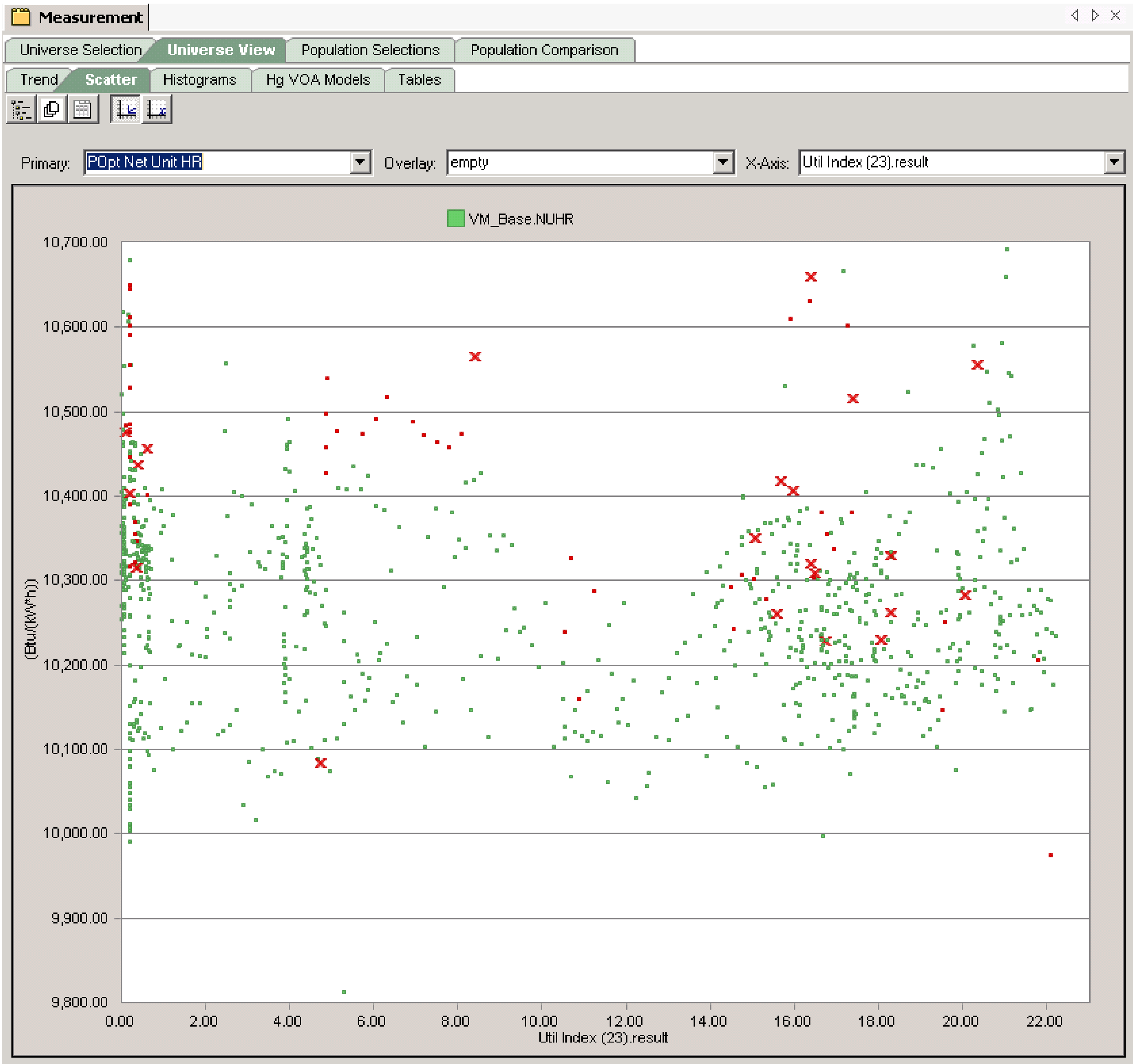

Figure 103: PerformanceOpt Net Unit Heat Rate vs. Broader Utilization Index (Util Index(23))

3.6.3.11 PerformanceOpt Net Turbine Heat Rate (Corrected)

Figure 104 shows PerformanceOpt's Net Turbine Heat Rate plotted with indices of utilization. Red samples indicate where PerformanceOpt's model did not converge. They were marked bad status and excluded from the estimate of means for population comparison.

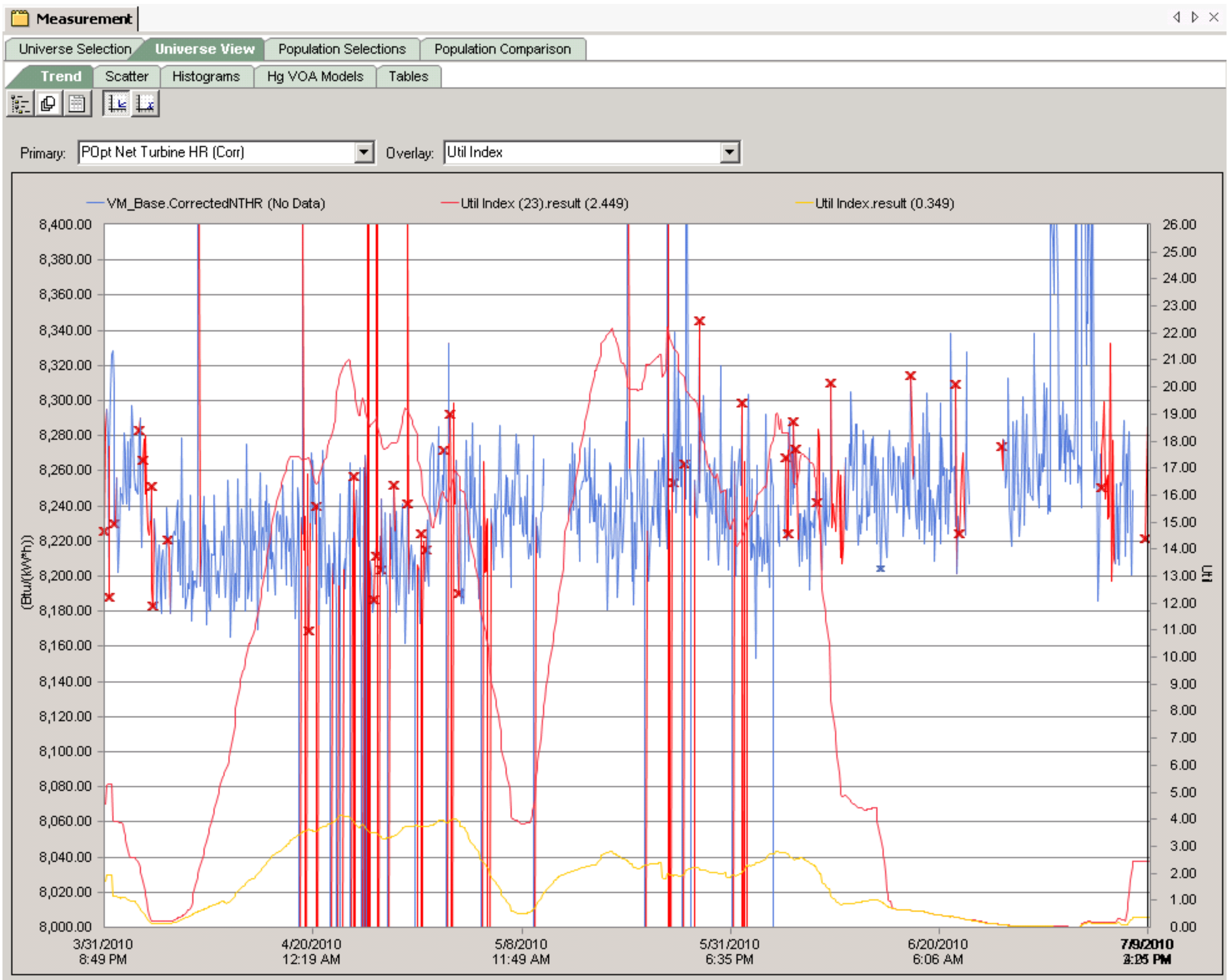

Figure 104: PerformanceOpt Net Turbine Heat Rate with utilization indices

Figure 105 shows PerformanceOpt's Net Turbine Heat Rate plotted vs. Util Index.

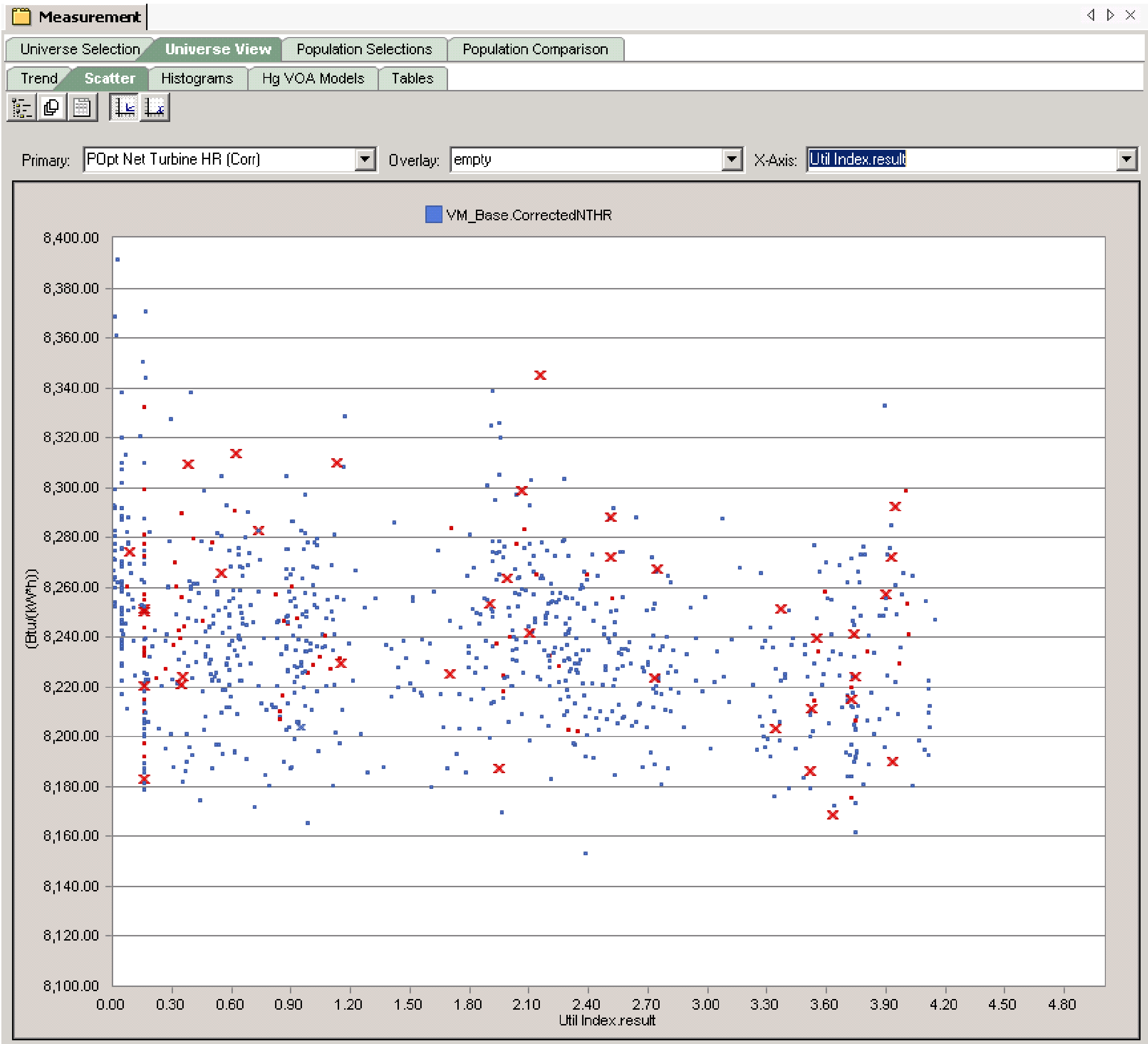

Figure 105: PerformanceOpt Net Turbine Heat Rate vs. Utilization Index

Figure 106 shows PerformanceOpt's Net Turbine Heat Rate vs. Util Index(23)

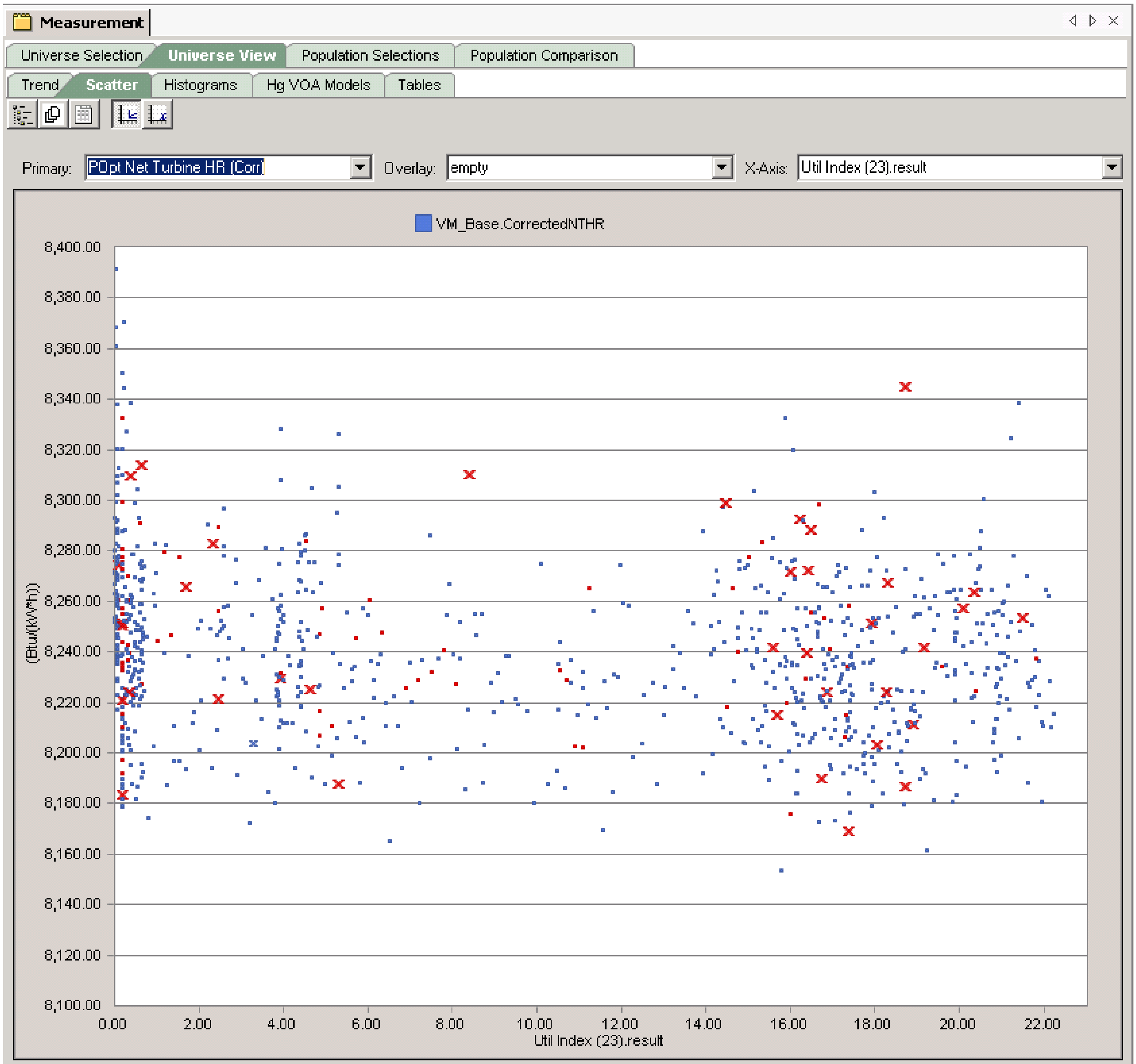

Figure 106: PerformanceOpt Net Turbine Heat Rate vs. Broader Utilization Index (Util Index(23)

3.6.3.12 PerformanceOpt Losses Efficiency

Figure 107 shows PerformanceOpt's Losses Boiler Efficiency plotted with indices of utilization. Red samples indicate where the PerformanceOpt model did not converge. They were marked bad status and excluded from the estimate of means for population comparison.

Figure 107: PerformanceOpt Losses Boiler Efficiency and Indices of Utilization

Figure 108 shows PerformanceOpt's Losses Boiler Efficiency vs. Util Index.

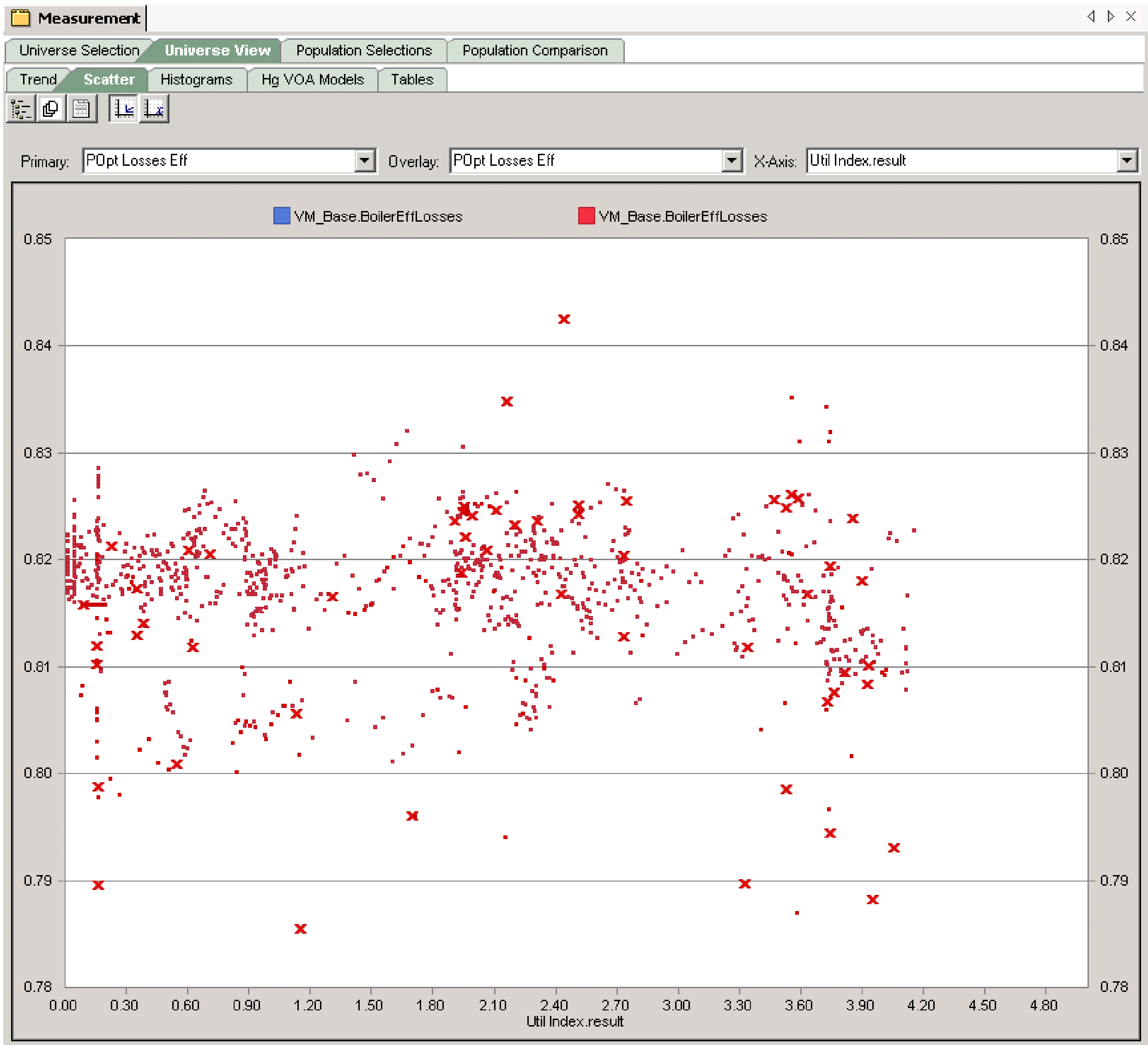

Figure 108: PerformanceOpt Losses Boiler Efficiency vs. Utilization Index

Figure 109 shows PerformanceOpt's Losses Boiler Efficiency vs. Util Index(23).

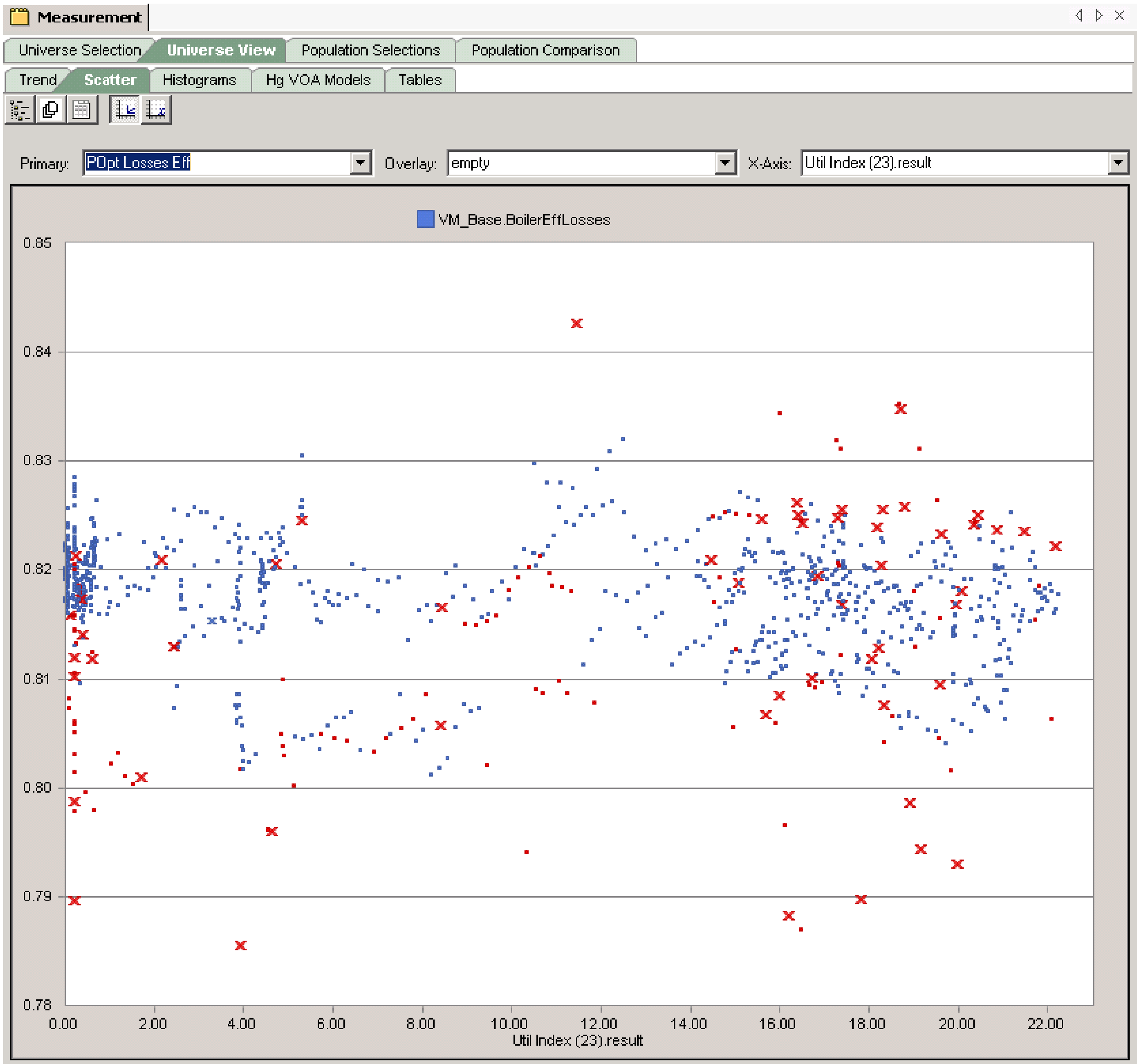

Figure 109: PerformanceOpt Losses Boiler Efficiency vs. Broader Index of Utilization (Util Index(23))

3.6.3.13 Condenser Back Pressure

Condenser back pressure represents a significant disturbance to Heat Rate and Efficiency estimates. Heat sink conditions, into which waste heat must be ejected, are represented by condenser back pressure, and have a major effect on the efficiency of the overall thermal cycle.

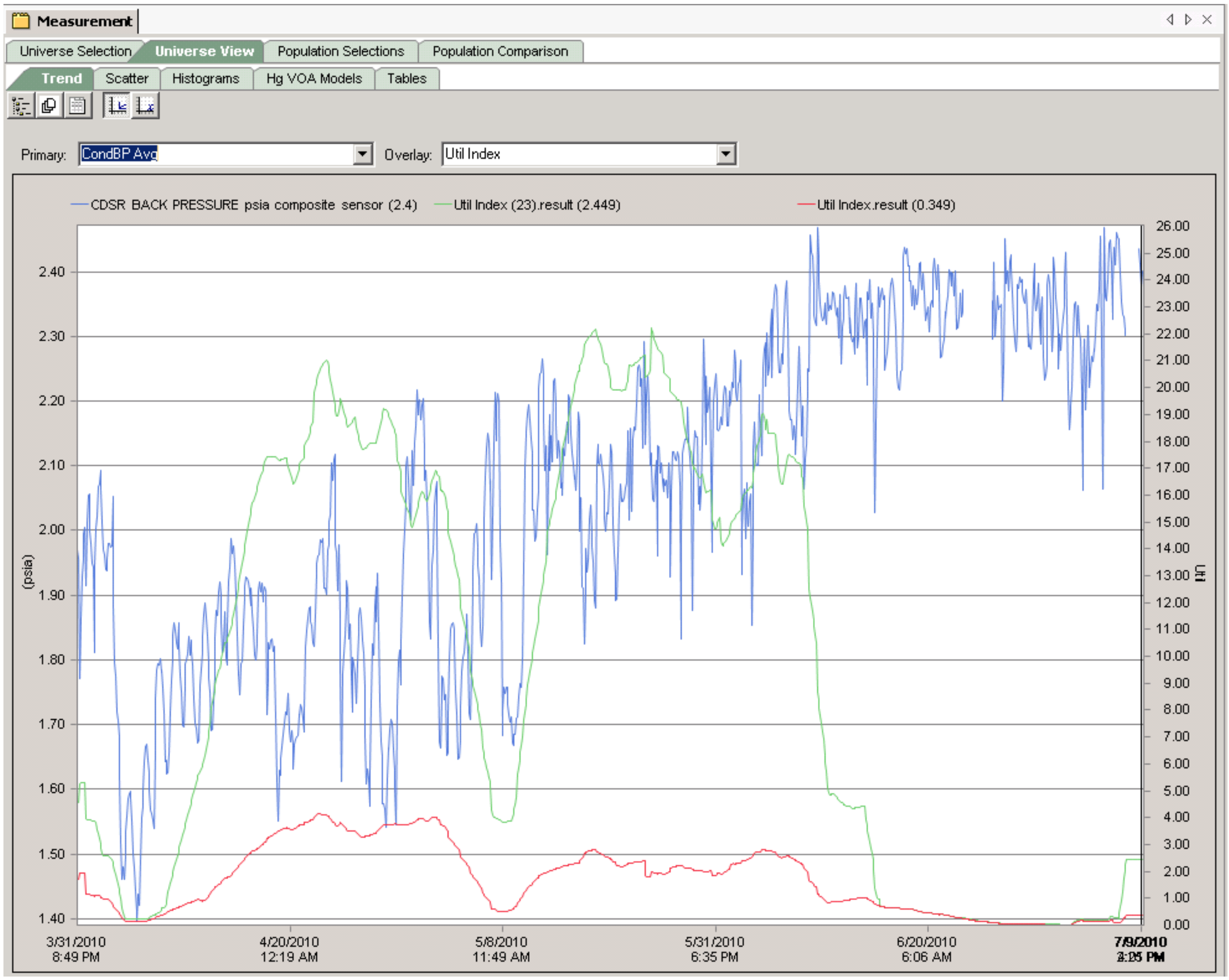

Figure 110: Condenser Backpressure with Indices of Utilization

Figure 111 shows PerformanceOpt Net Unit Heat Rate plotted vs. Condenser Back Pressure. The upward trend indicates that a positive correlation exists, and higher back pressure was correlated to higher heat rate, which was an expected result. Higher ambient thermal energy inhibits efficient heat rejection.

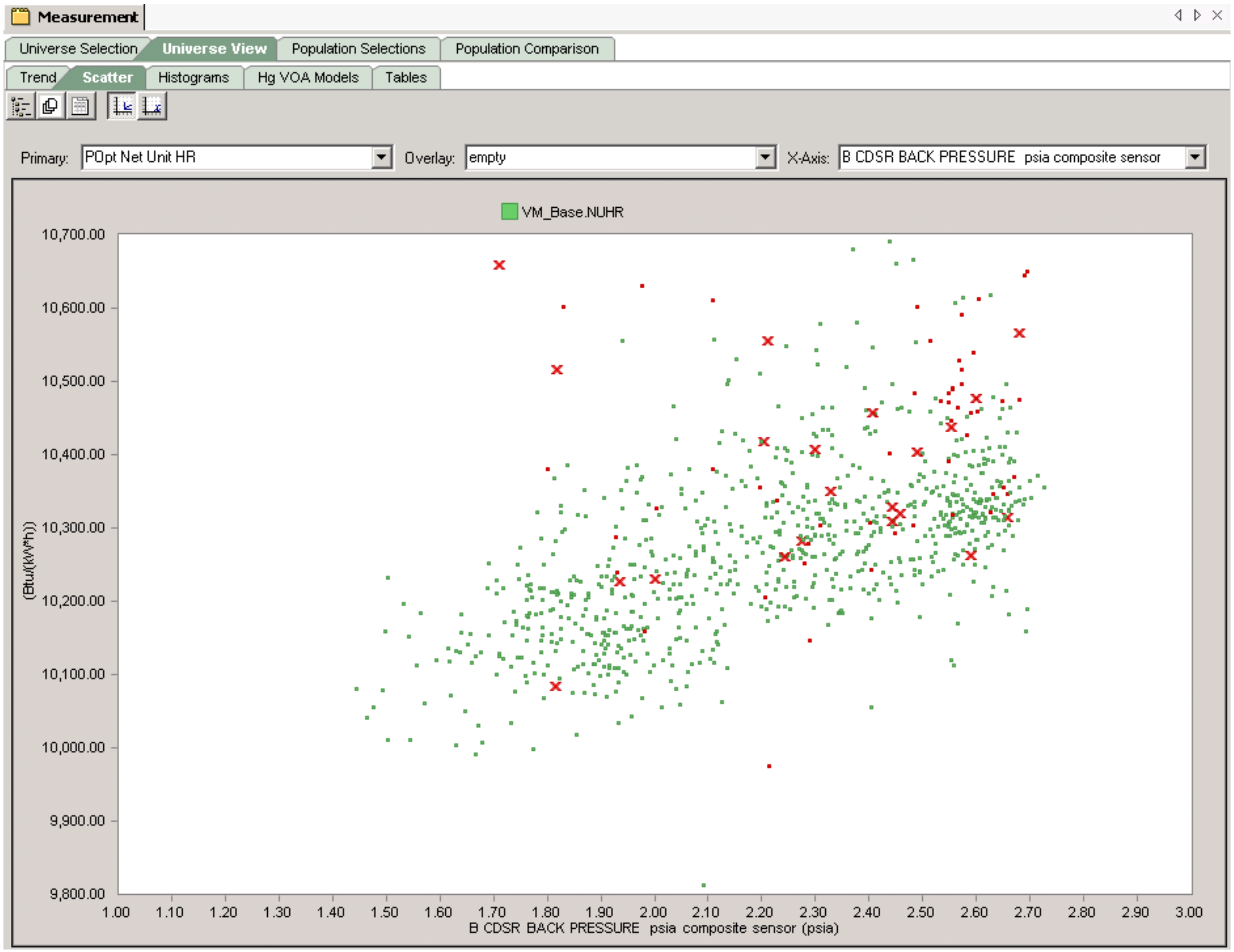

Figure 111: PerformanceOpt Net Unit Heat Rate vs. Condenser Back Pressure

Figure 112 shows PerformanceOpt Net Turbine Heat Rate plotted vs. Condenser Back Pressure. Corrected Turbine Heat Rate should be significantly less affected by condenser back pressure, because it's value is corrected to "design conditions", though a causal relationship cannot be ruled out, and must be considered as a possible cause for any apparent correlation.

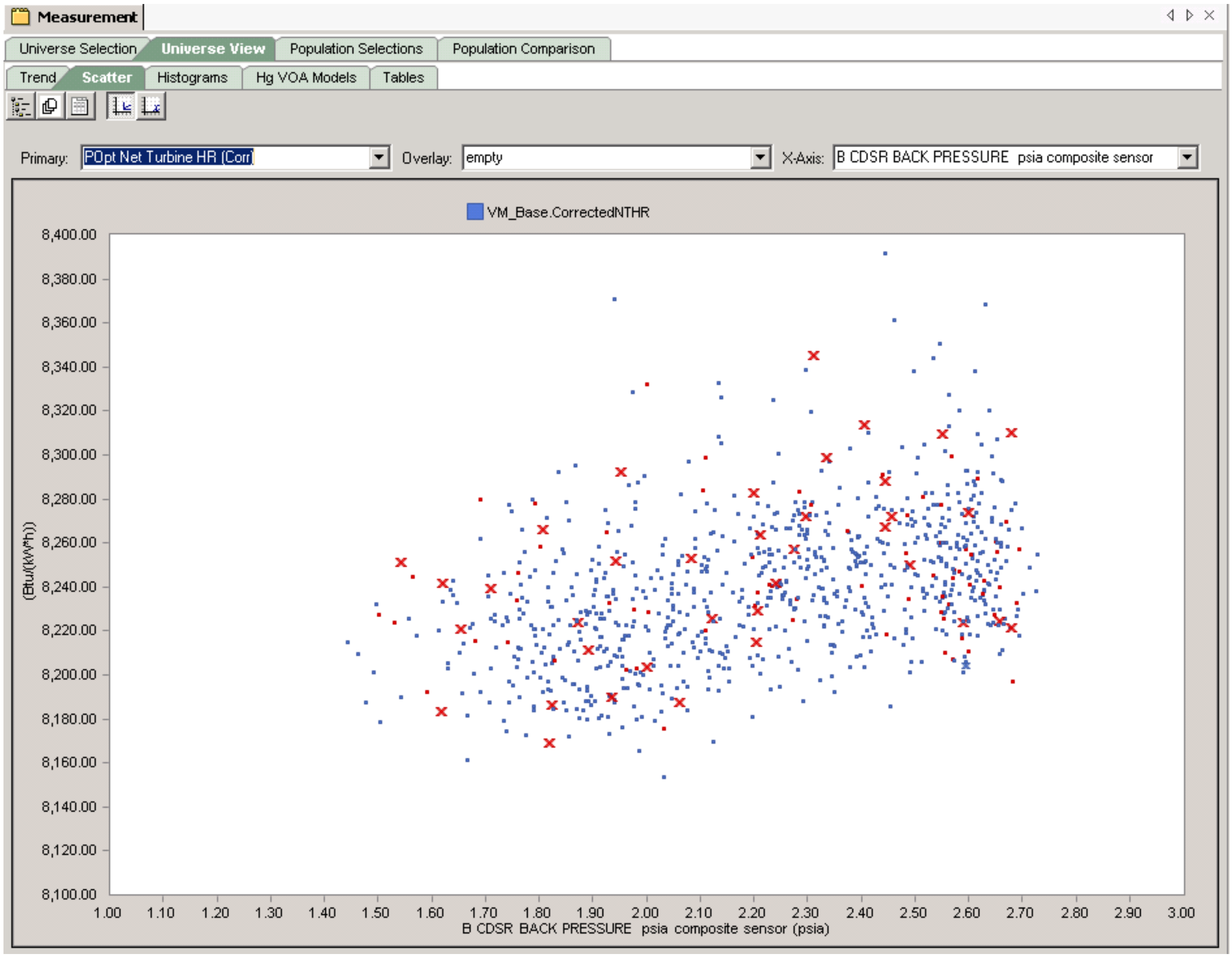

Figure 112: PerformanceOpt Net Turbine Heat Rate vs. Condenser Back Pressure

Figure 113 shows PerformanceOpt Losses Boiler Efficiency plotted vs. Condenser Back Pressure. Losses efficiency should be relatively unaffected by Condenser Back Pressure itself but can be affected by changes in ambient temperature, which is the major driver for changes to condenser back pressure, along with condenser cleanliness. Higher ambient temperatures lead to higher condenser back pressures. The effect on losses efficiency is less straightforward.

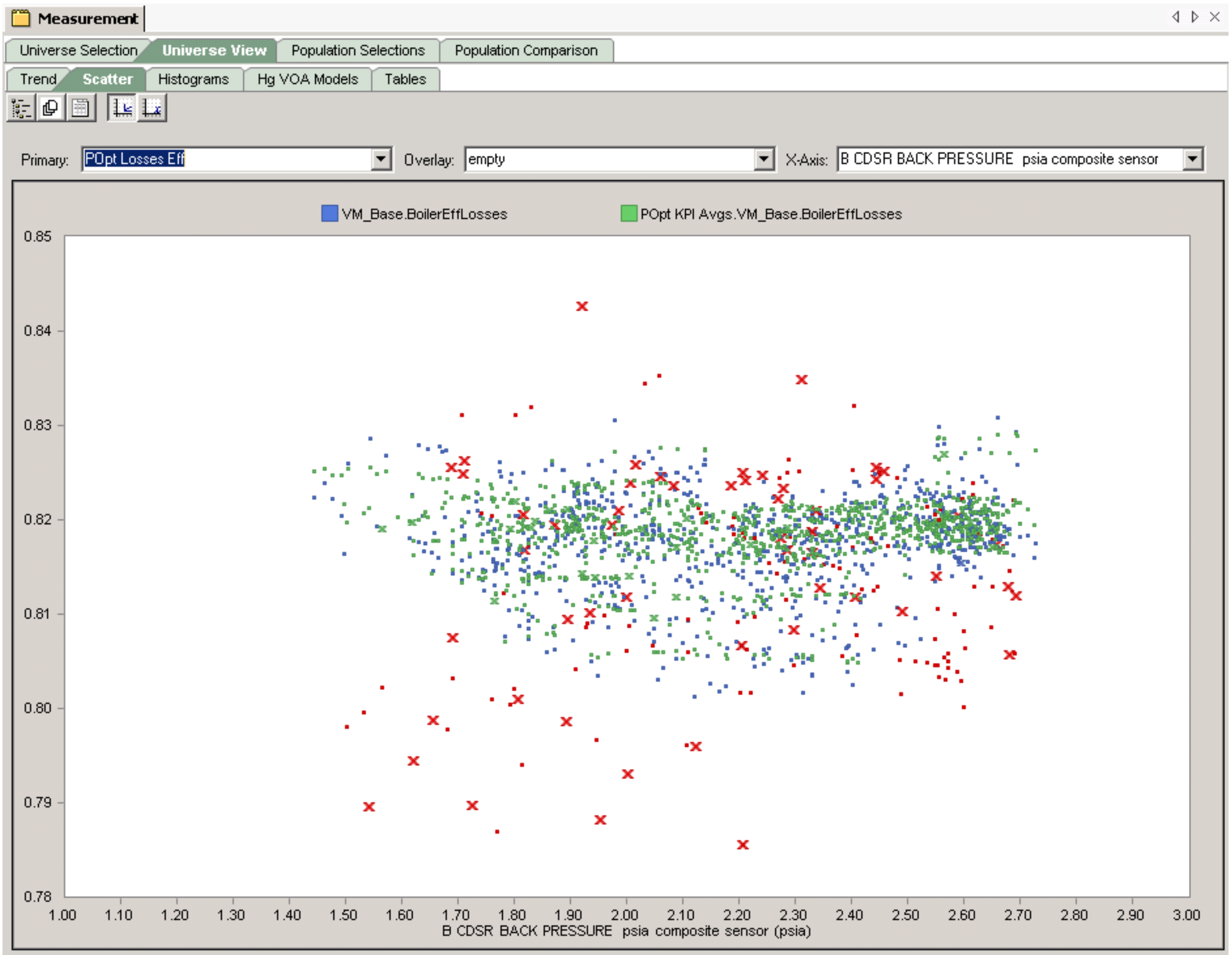

Figure 113: PerformanceOpt Losses Boiler Efficiency vs. Condenser Back Pressure

3.6.4 Patterns of Utilization

Operators have complete discretion over when and what parts of the optimization system get enabled. This approach is critical to operational safety and an important commitment to supporting the operator's accountability for unit operations and respecting their wisdom regarding just how the unit should be run. That said, significant variability exists in perspective among unit crews, which consist of typically more than a dozen individuals. Further significant variability exists in the relationship between operators and other groups at the plant. These groups include various permutations of performance engineering teams, production leaders and supervisors, and production management staff. No two units, even within the same utility or occasionally the same site, are the same.

Optimization and on-line analytics, like all other engineering tools, is only as good as the user. If used well, they have been proven to deliver real benefits that justify not just the cost of acquiring the technology but also the cost of using it, which of course is non-zero. In every case the key to "good use" is bi-directional transfer of knowledge. Plant operations, control and performance staff need to be educated about how the technology works, what it can and cannot do, what its weaknesses and strengths are, so that: a) their expectations are grounded in specifics, b) they understand the dimensions in which action can be taken to get the most from the tool, and to address issues that may emerge, and c) they can communicate effectively what they want to those who are more familiar with the technology than the plant. Vendor staff and outsourced utilization staff need to gain specific knowledge of the unit in question and the operational specifics of the site so the issues that are obvious to plant staff can be made clear to them and solutions found in an efficient manner. There need to be clear paths and hierarchies of communication and accountability, and clear processes for monitoring and measuring success objectively.

Deployment and utilization planning, whereby the commissioning and on-going use of the technology is planned across the specific architecture of a given plant and/or unit is a way of increasing the probability that good utilization will occur, and benefits realized. This planning includes resource and time allocation, continued commitments to training on the part of both the vendor and the site, clear definitions of success, clear points and persons of accountability, clear contingencies in the event of staff turnover, and specific processes to support all of these.

In many cases it is simply not feasible for the plant to take on significant aspects of the work required to achieve high quality utilization, either due to gaps in the somewhat specialized skill-set, or to a sheer lack of personnel. In such cases, a cost-benefit analysis needs to be presented that justifies outsourcing some significant aspects of the utilization challenge. In almost all cases solutions exist, and only consideration and planning are needed to access them.

This section looks at the utilization indices, their relationship to each other, and the apparent relationship of their individual component objectives. This kind of analysis can help to identify the optimization system components that may be having the most positive effect, and those that may be hindering performance, questions which must be answered at each site.

Knowledge gleaned from such analyses can be converted through joint consideration representing the plant and vendor perspective, into action that can improve optimizer performance and utilization.

Figure 114 shows the Utilization Index and its components. As indicated before, an index of utilization that provides a rough measure of to what degree optimization is active at a given time. Higher values of utilization index indicate more optimization was occurring.

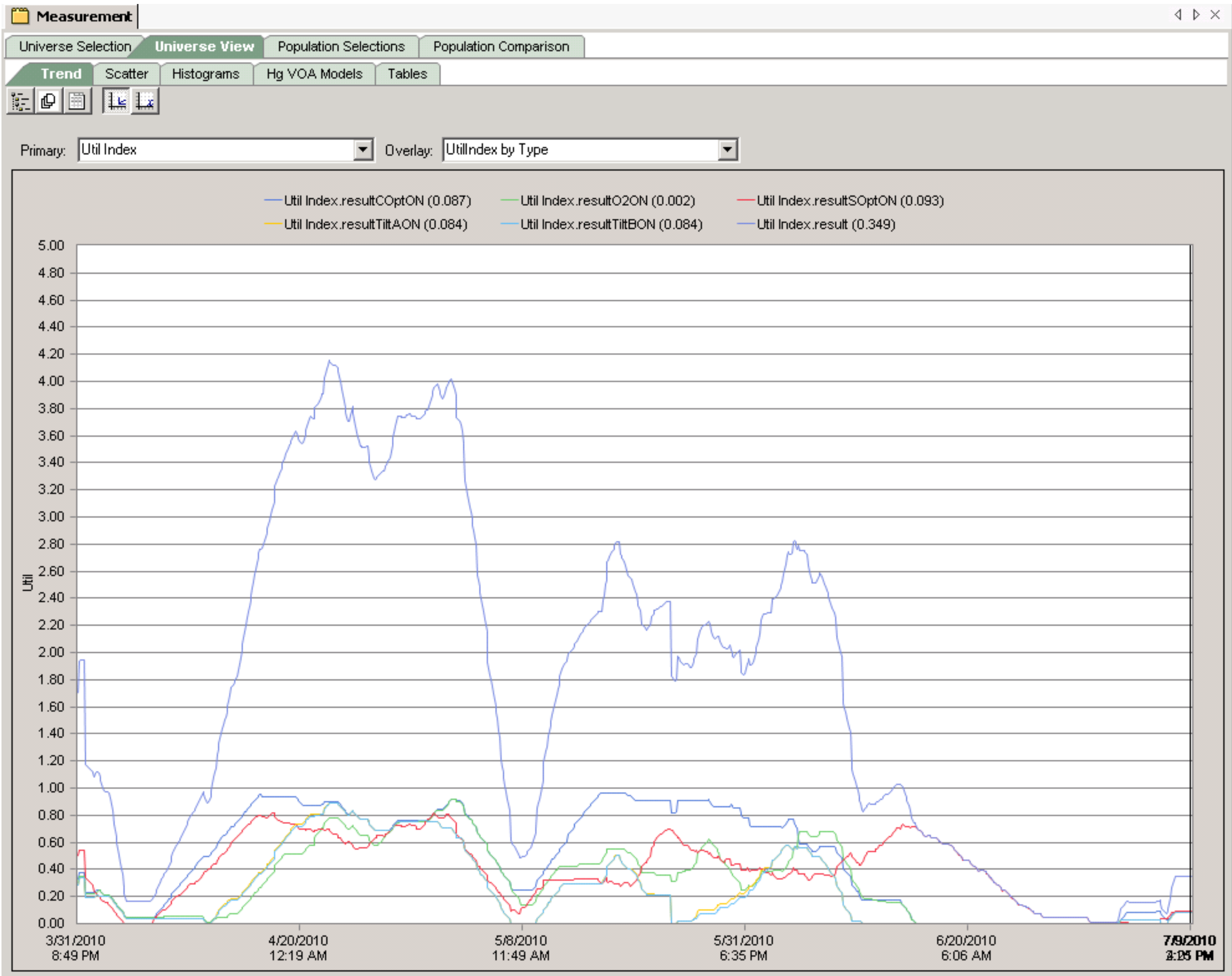

Figure 114: Utilization Index and Components

Figure 115 shows the Util Index(23), the broader index of combustion optimizer utilization, and its components.

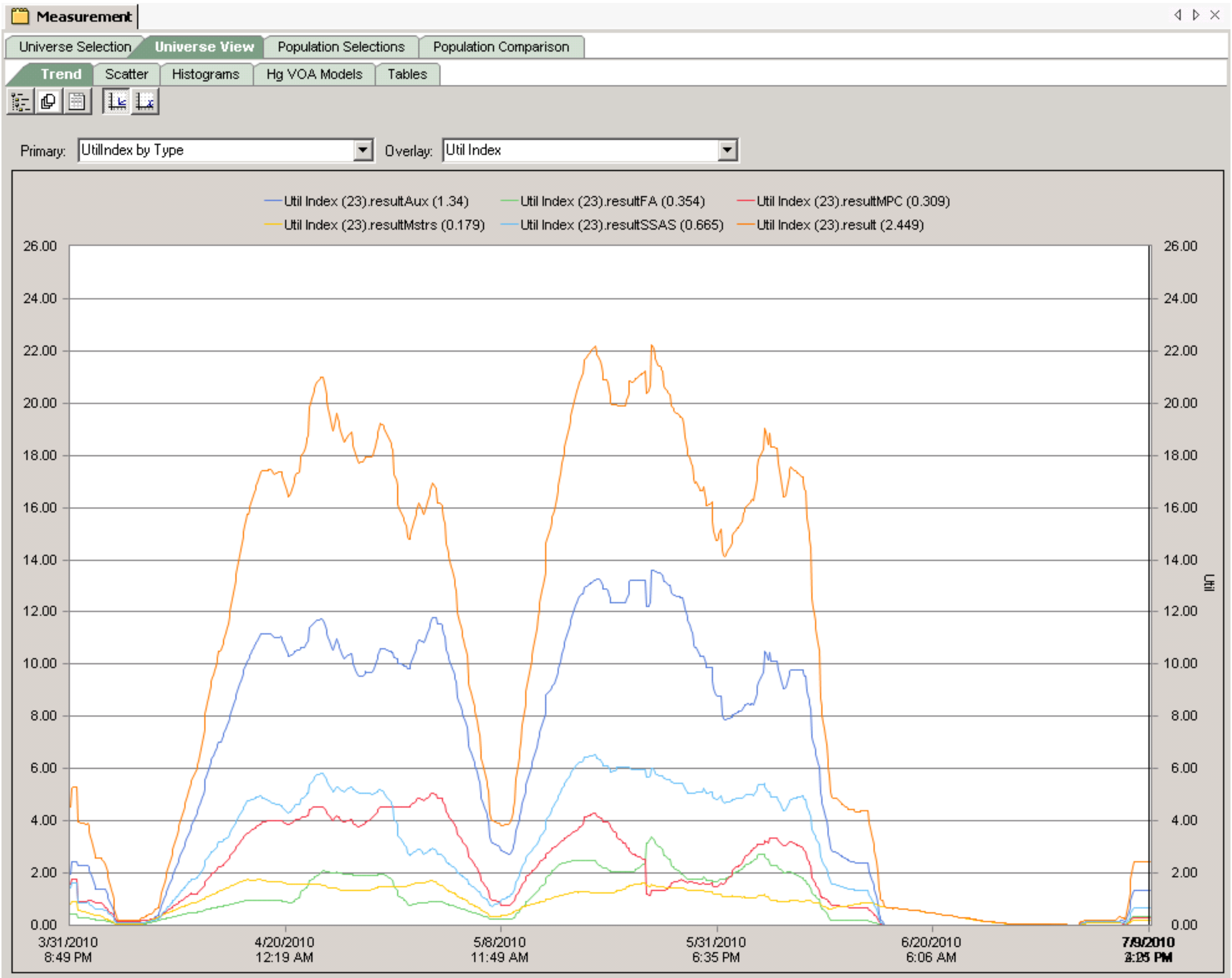

Figure 115: Broader Utilization Index (Util Index(23)) and Components

Figure 116 shows the two utilization indices plotted against each other to show that they are highly correlated but distinct.

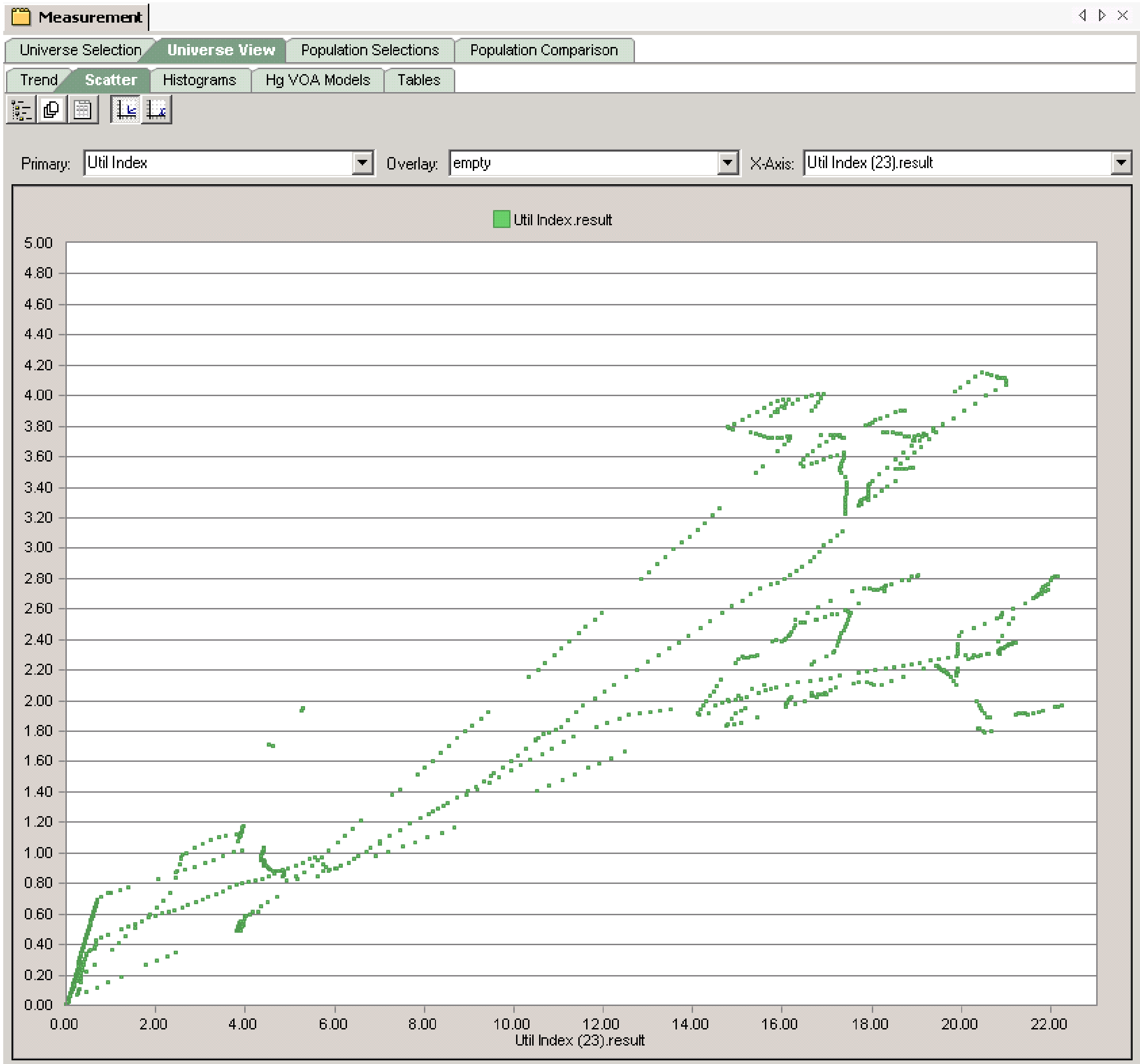

Figure 116: Util Index vs. Util Index(23)

3.6.4.1 Mercury Removal vs. Components of Utilization

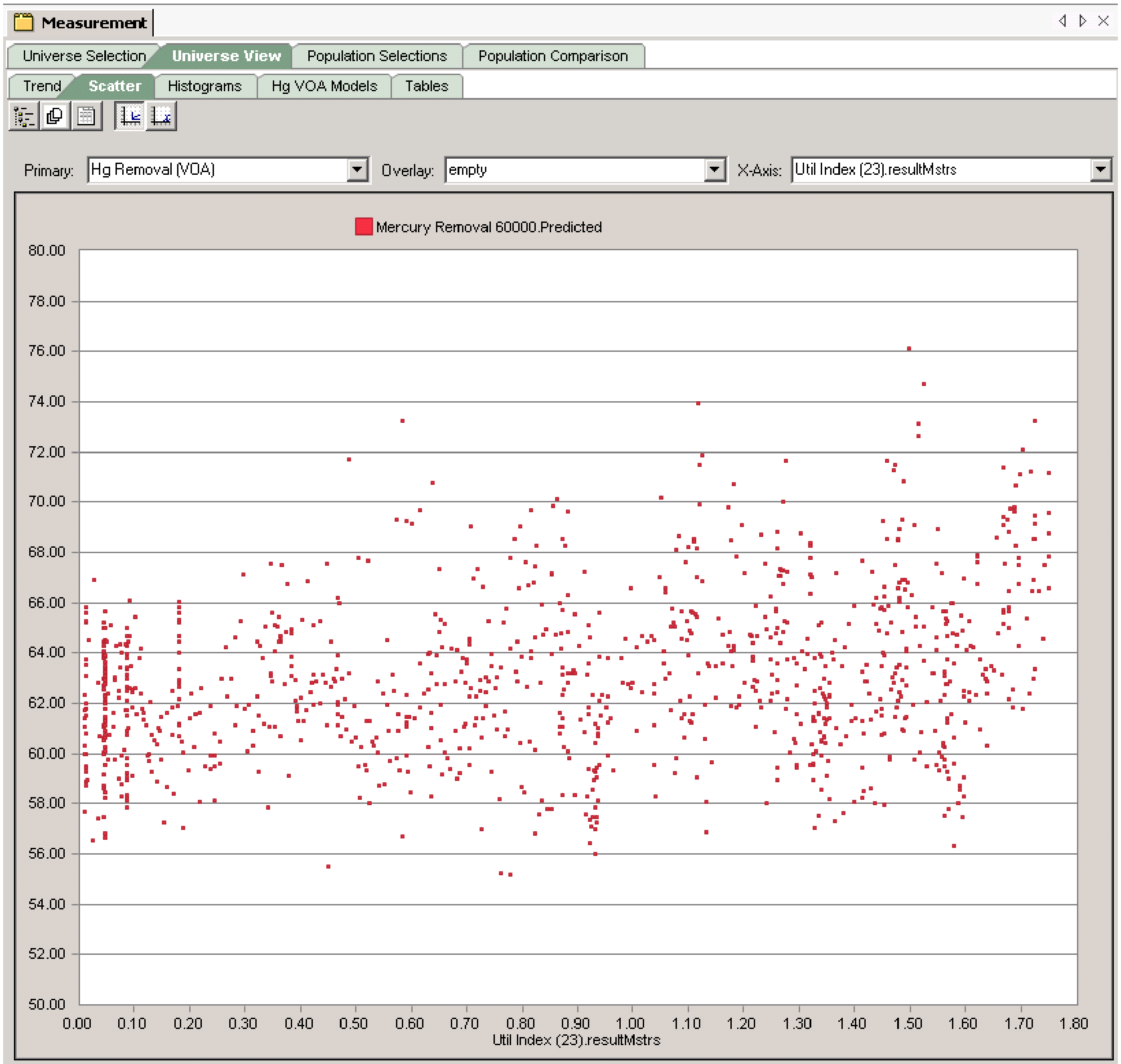

Figure 117: VOA Predicted Mercury Removal vs. Util Index (23), Master CombustionOpt and SootOpt enables

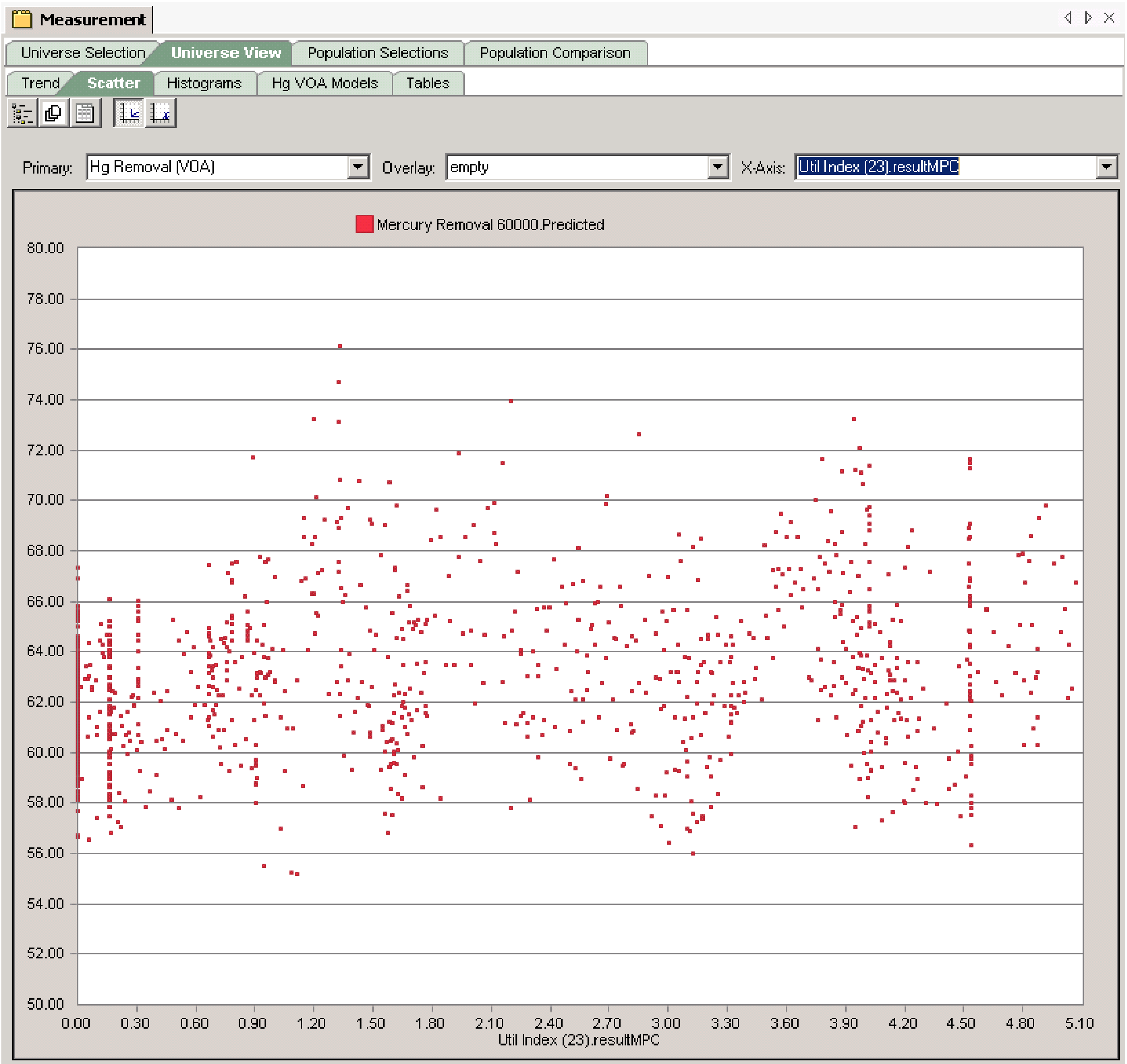

Figure 118: VOA Predicted Mercury Removal vs. Util Index(23) MPC MV's enable result

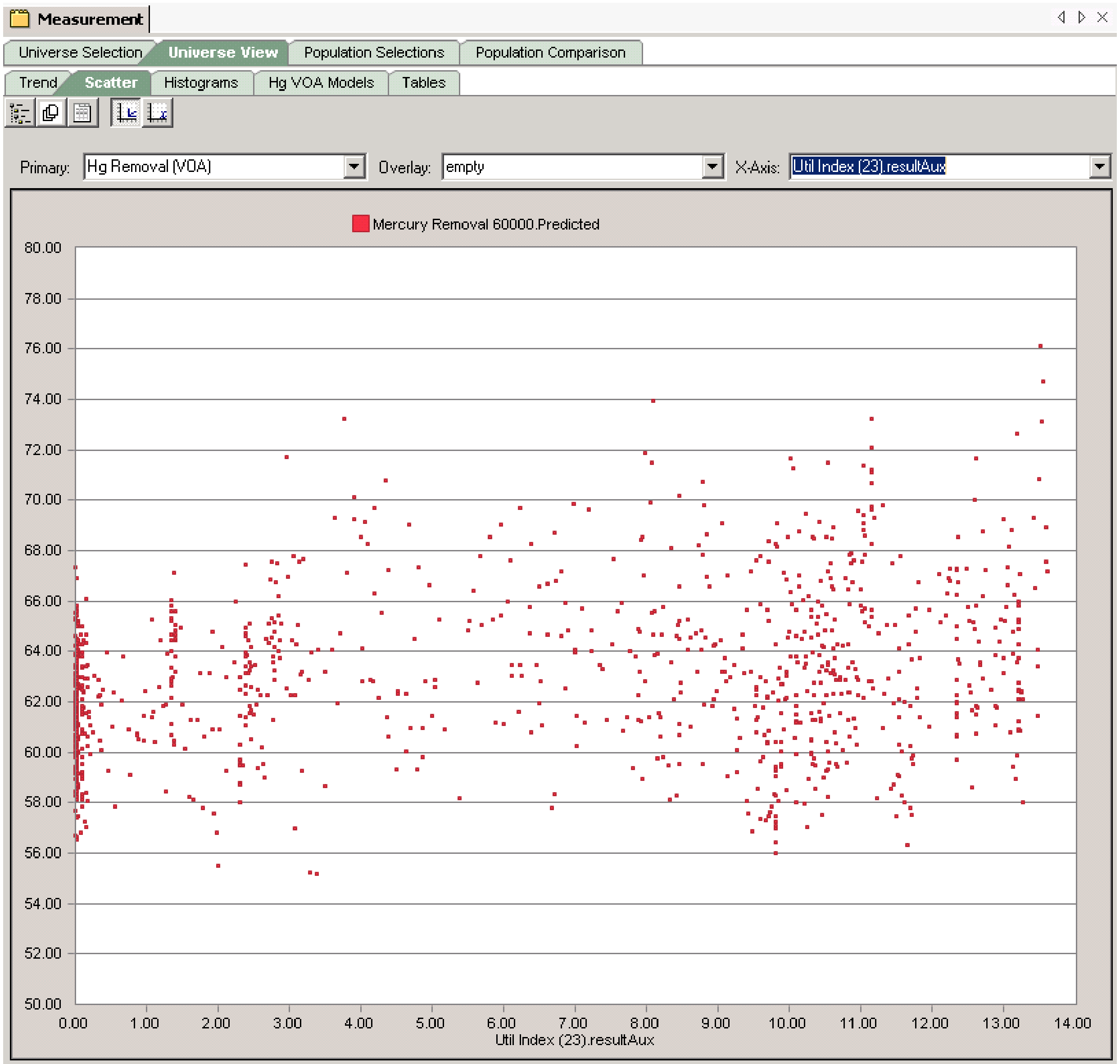

Figure 119: VOA Predicted Mercury Removal vs. Util Index(23) Aux Air MV's enable result

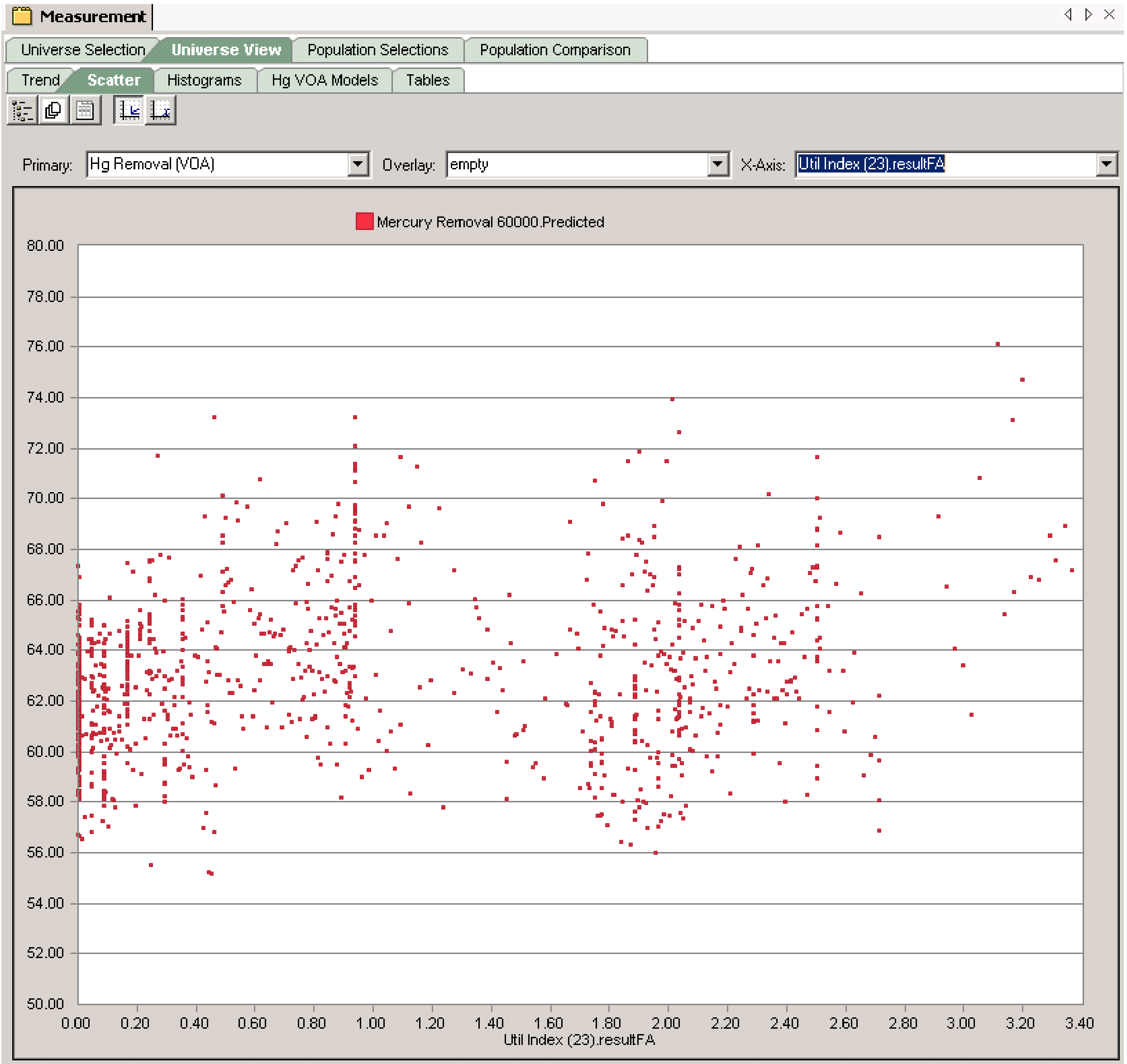

Figure 120: VOA Predicted Mercury Removal vs. Util Index(23) Fuel Air MV's enable result

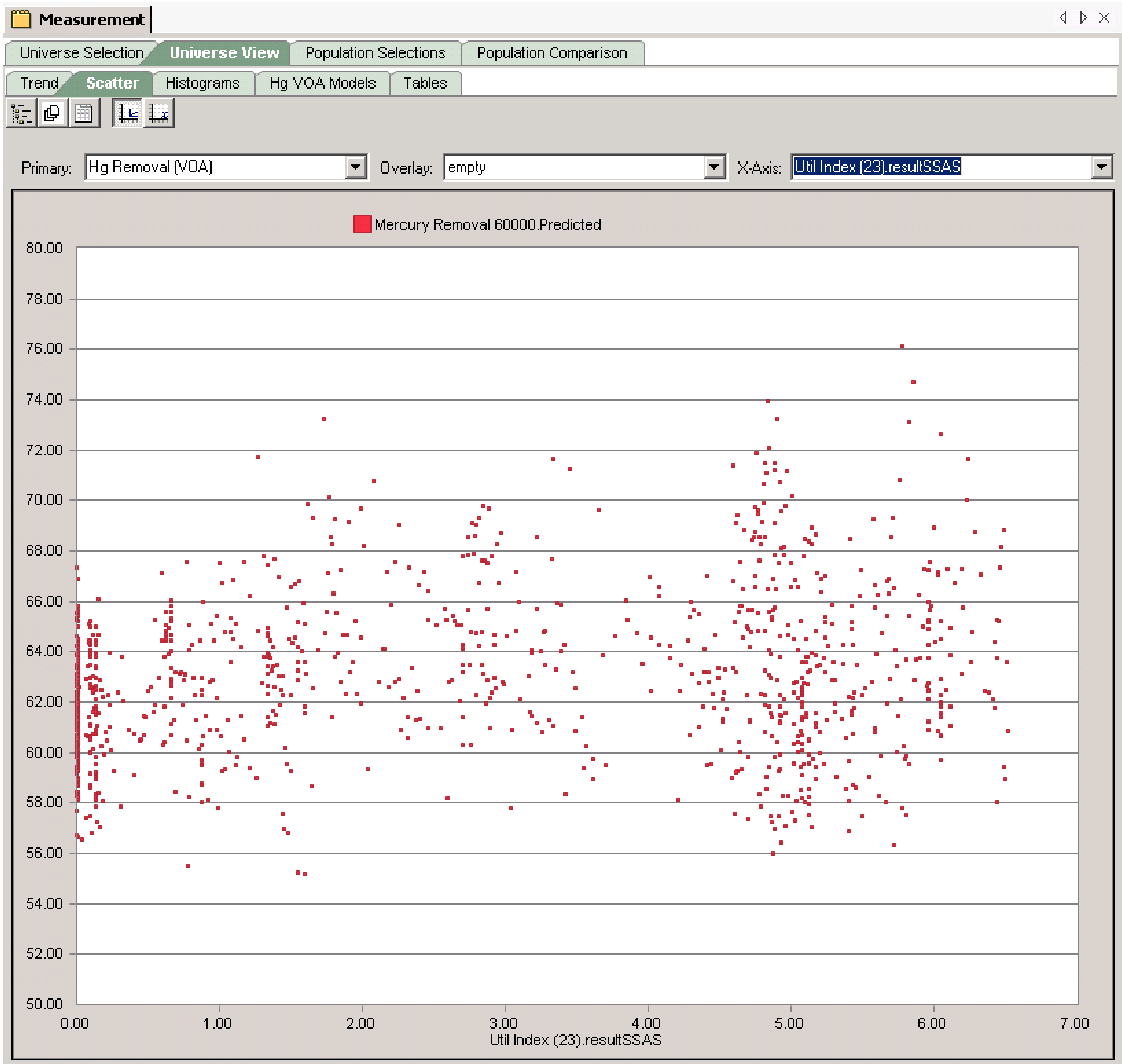

Figure 121: VOA Predicted Mercury Removal vs. Util Index(23) SSAS (Overfire Air) MV's enable result

3.6.4.2 Stack Total Mercury vs. Components of Utilization

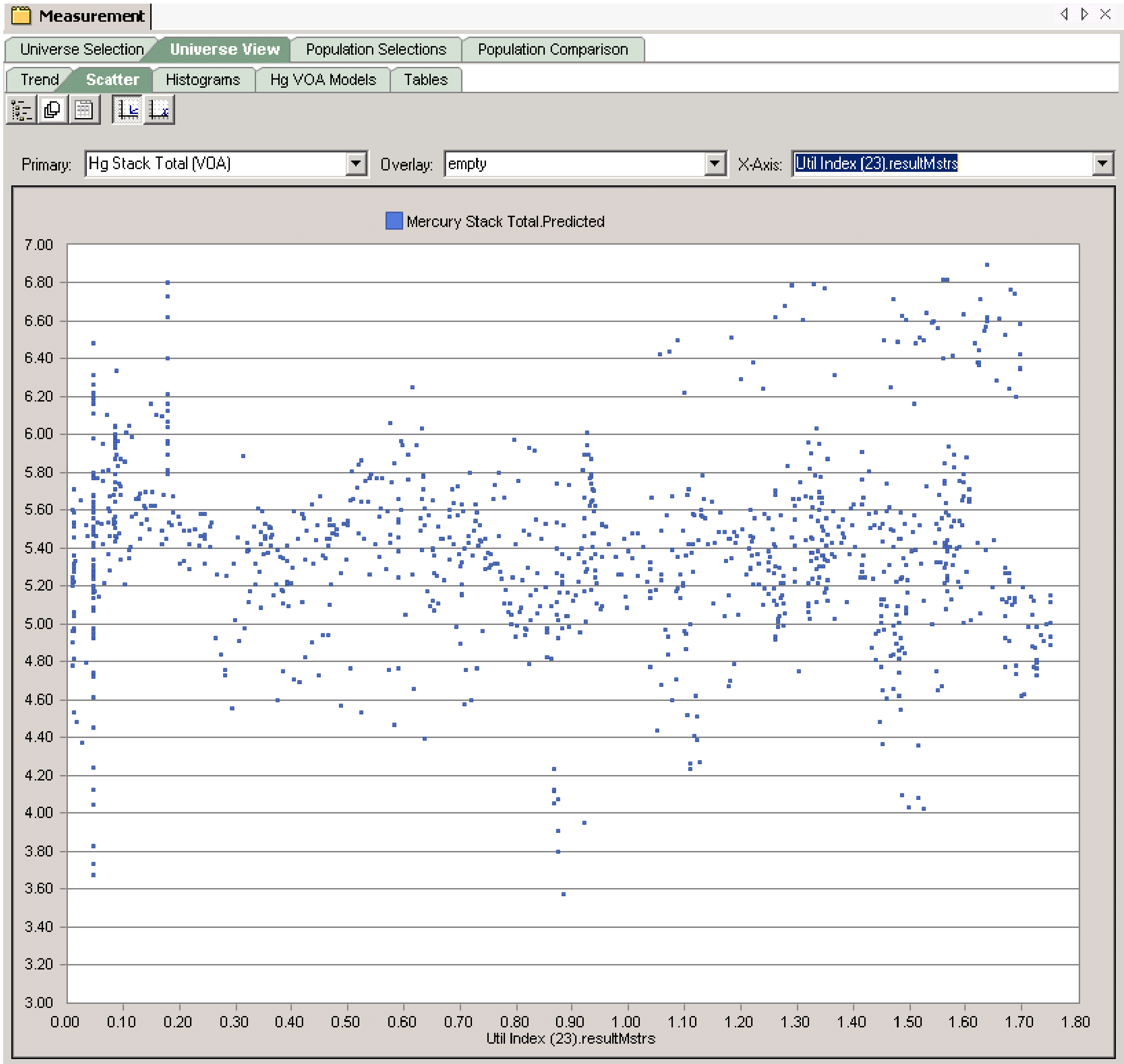

Figure 122: VOA Predicted Mercury Stack Total vs. Util Index(23) Master enable result

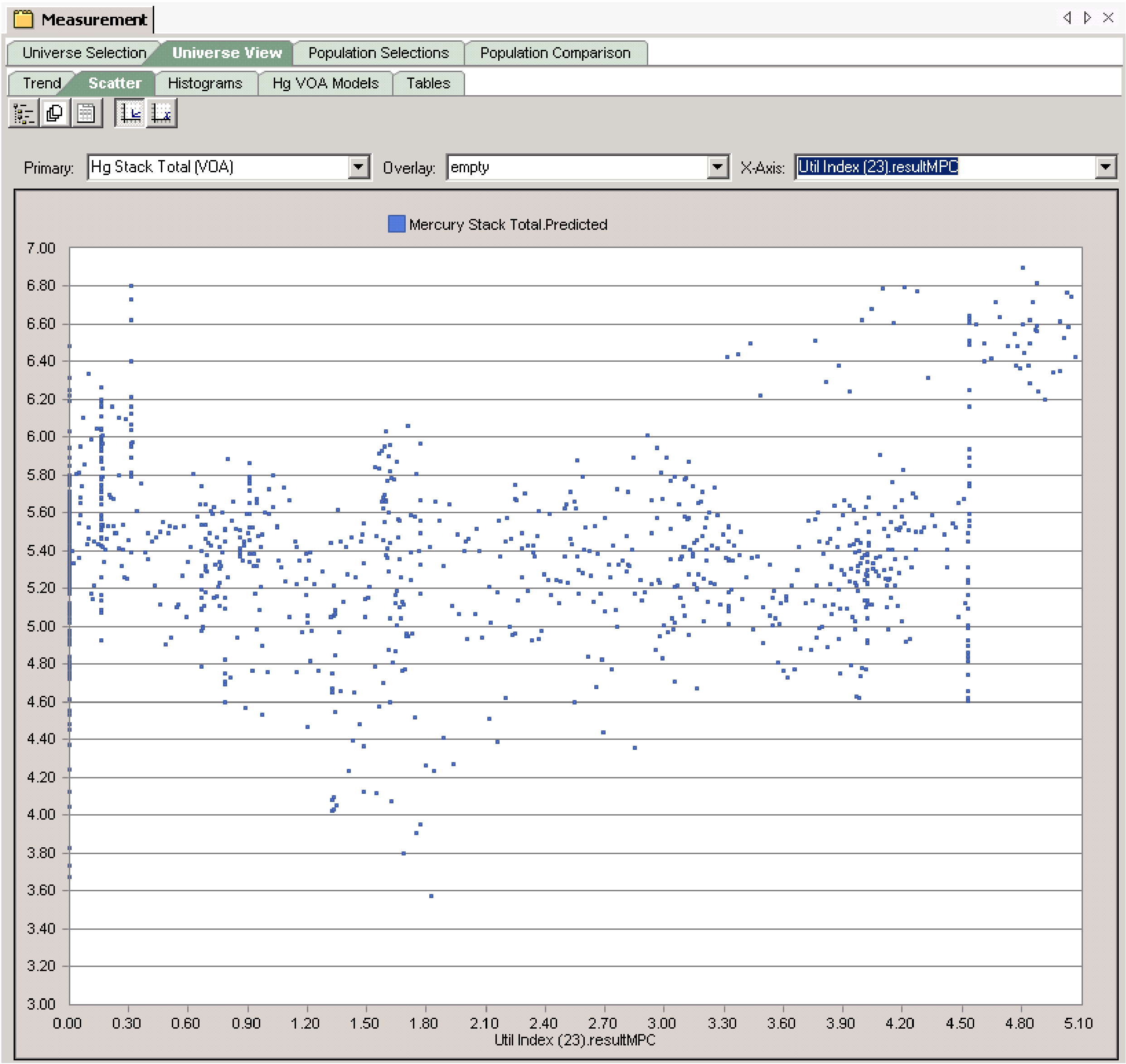

Figure 123: VOA Predicted Mercury Stack Total vs. Util Index(23) MPC MVs enable result

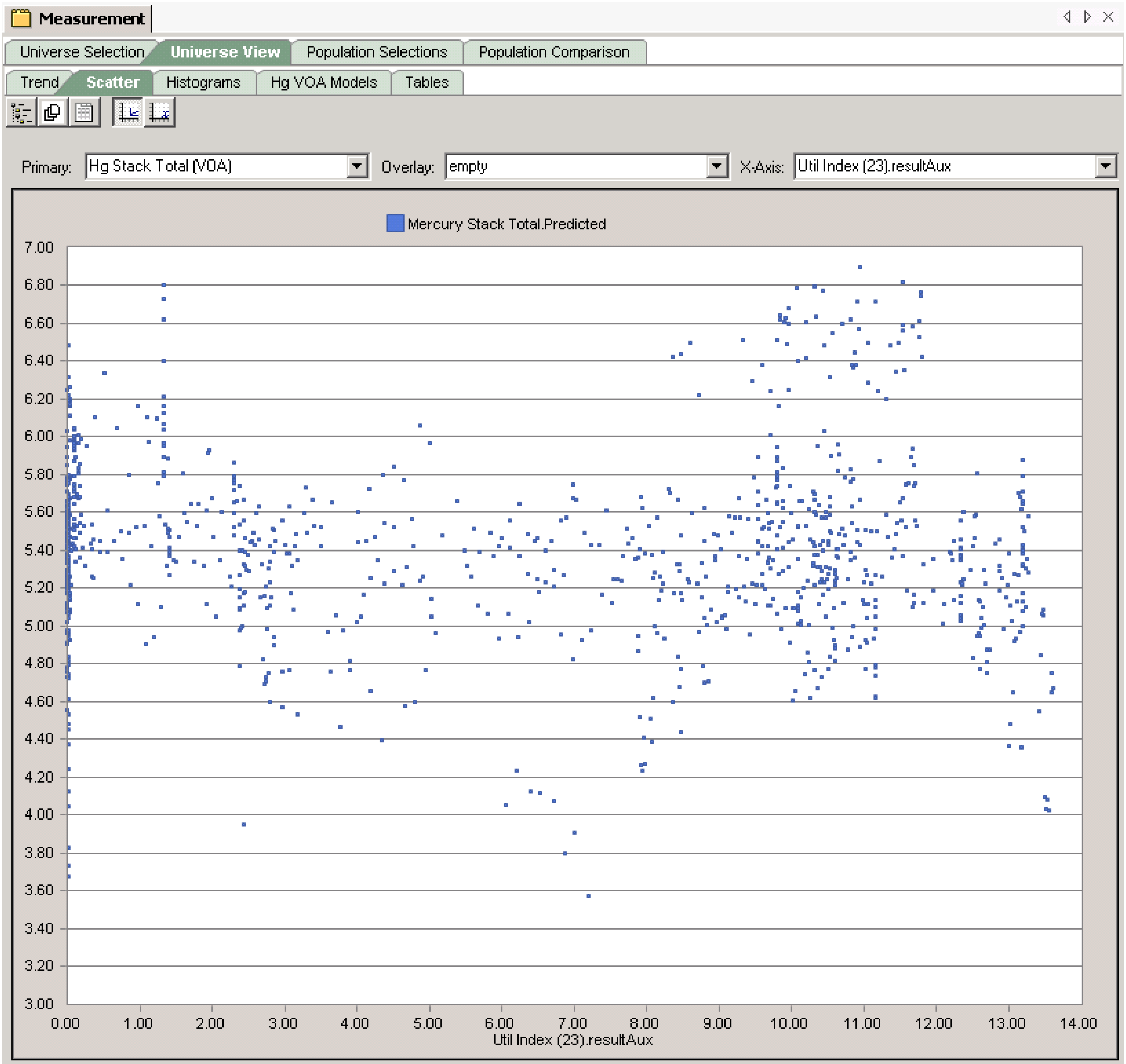

Figure 124: VOA Predicted Mercury Stack Total vs. Util Index(23) Aux Air MV's enable result

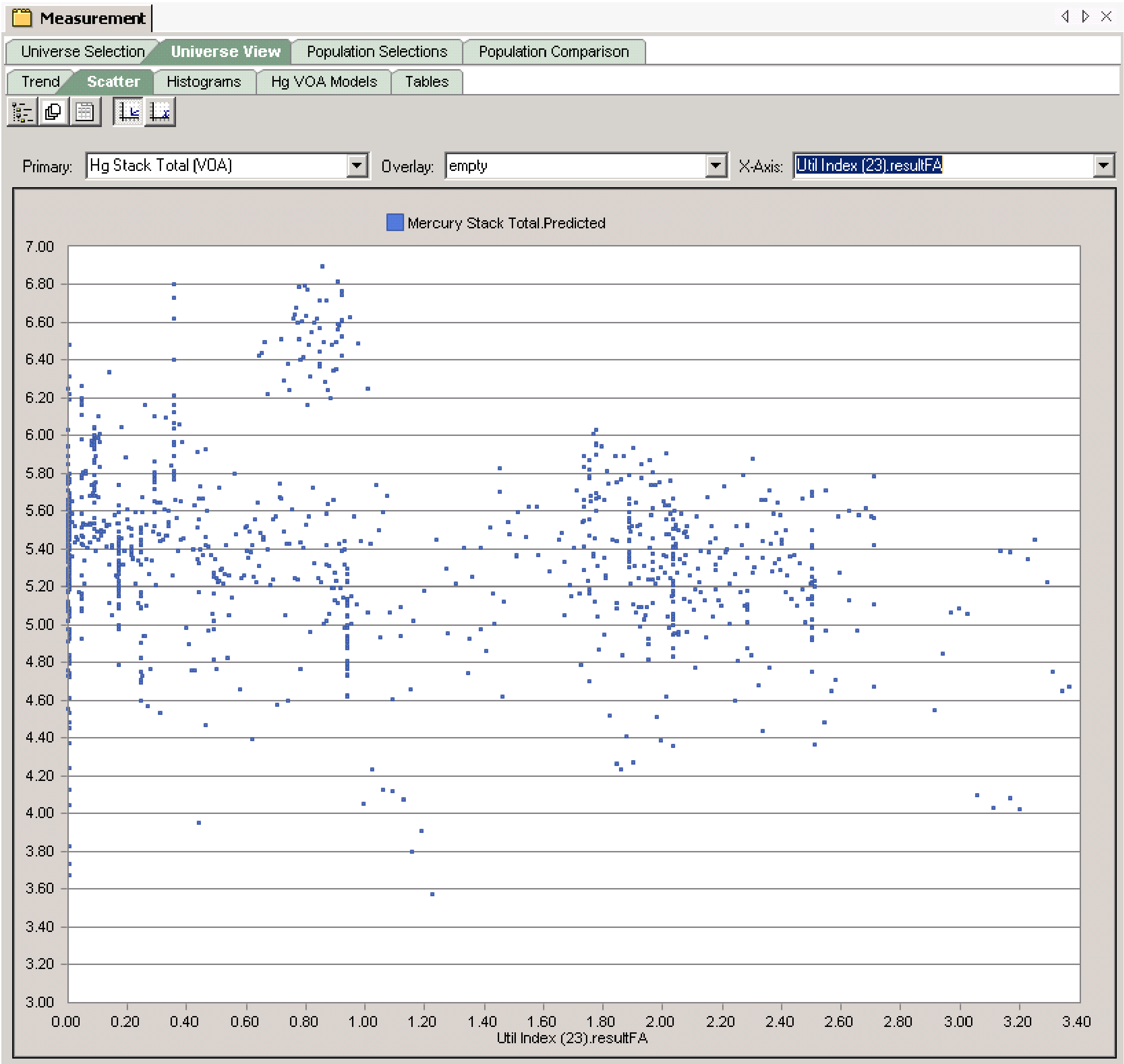

Figure 125: VOA Predicted Mercury Stack Total vs. Util Index(23) Fuel Air MV's enable result

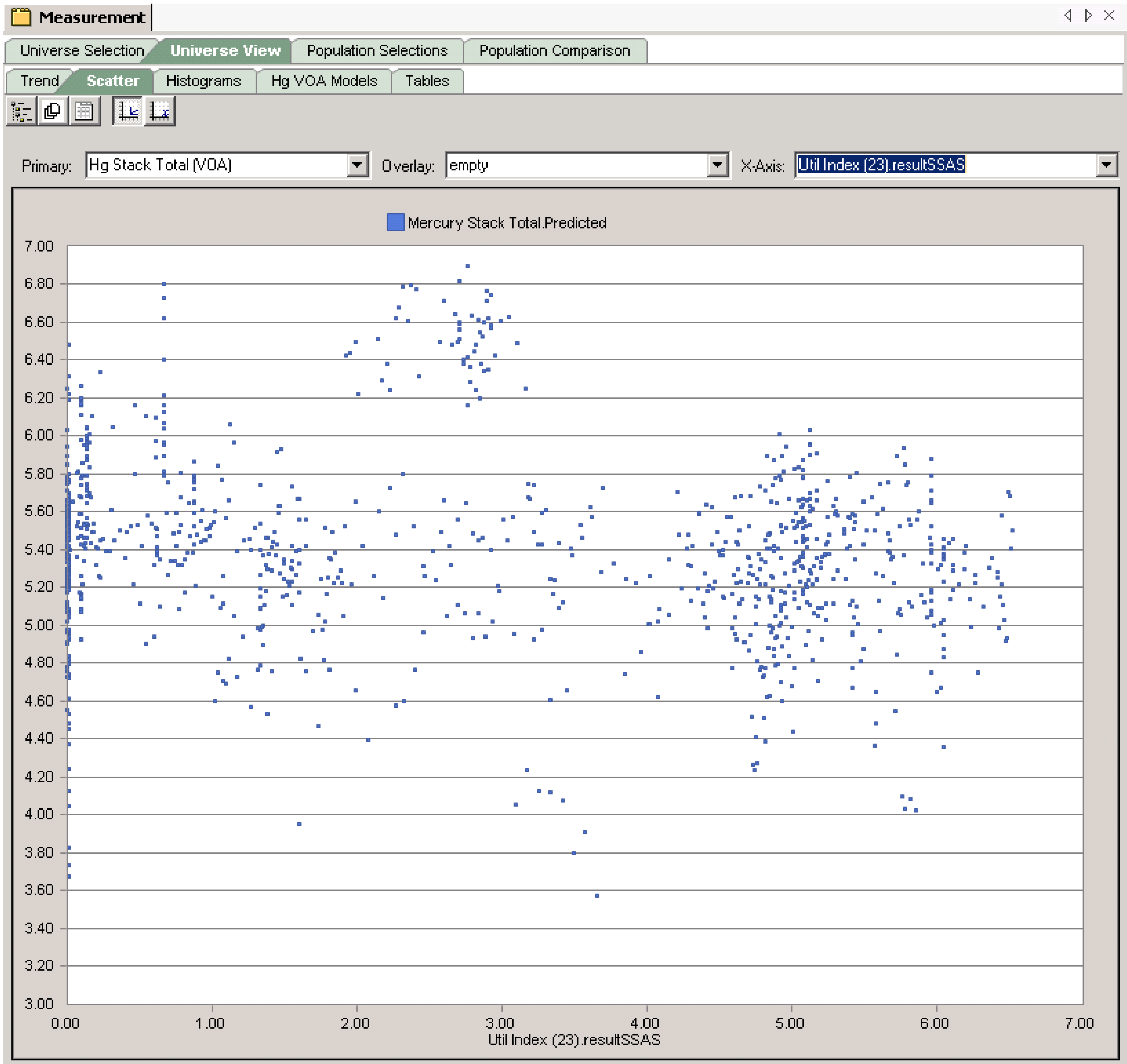

Figure 126: VOA Predicted Mercury Stack Total vs. Util Index(23) SSAS (Overfire Air) enable result

3.6.4.3 CEMS NOx vs. Components of Utilization

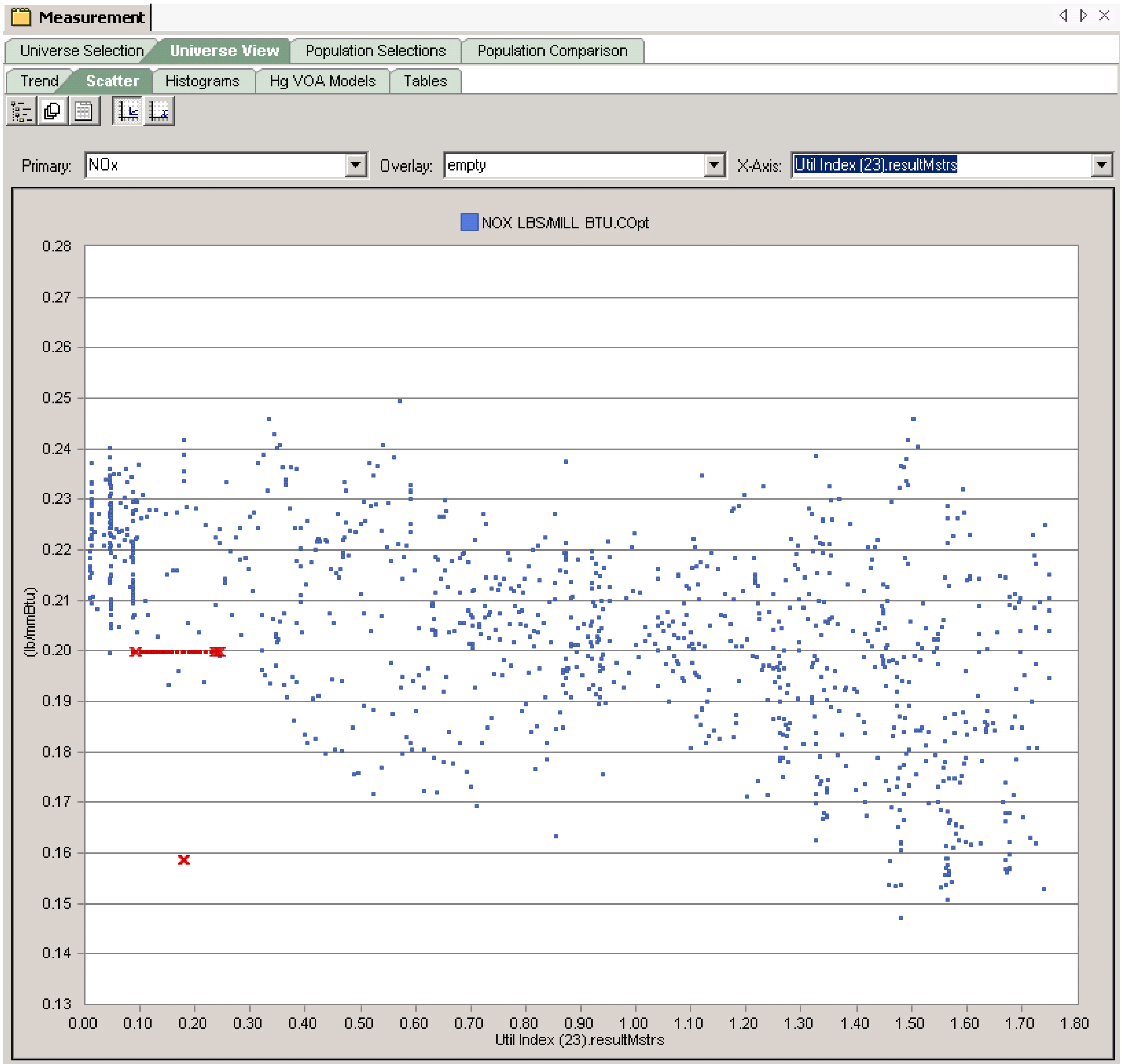

Figure 127: CEMS NOx vs. Util Index(23) Master enable result

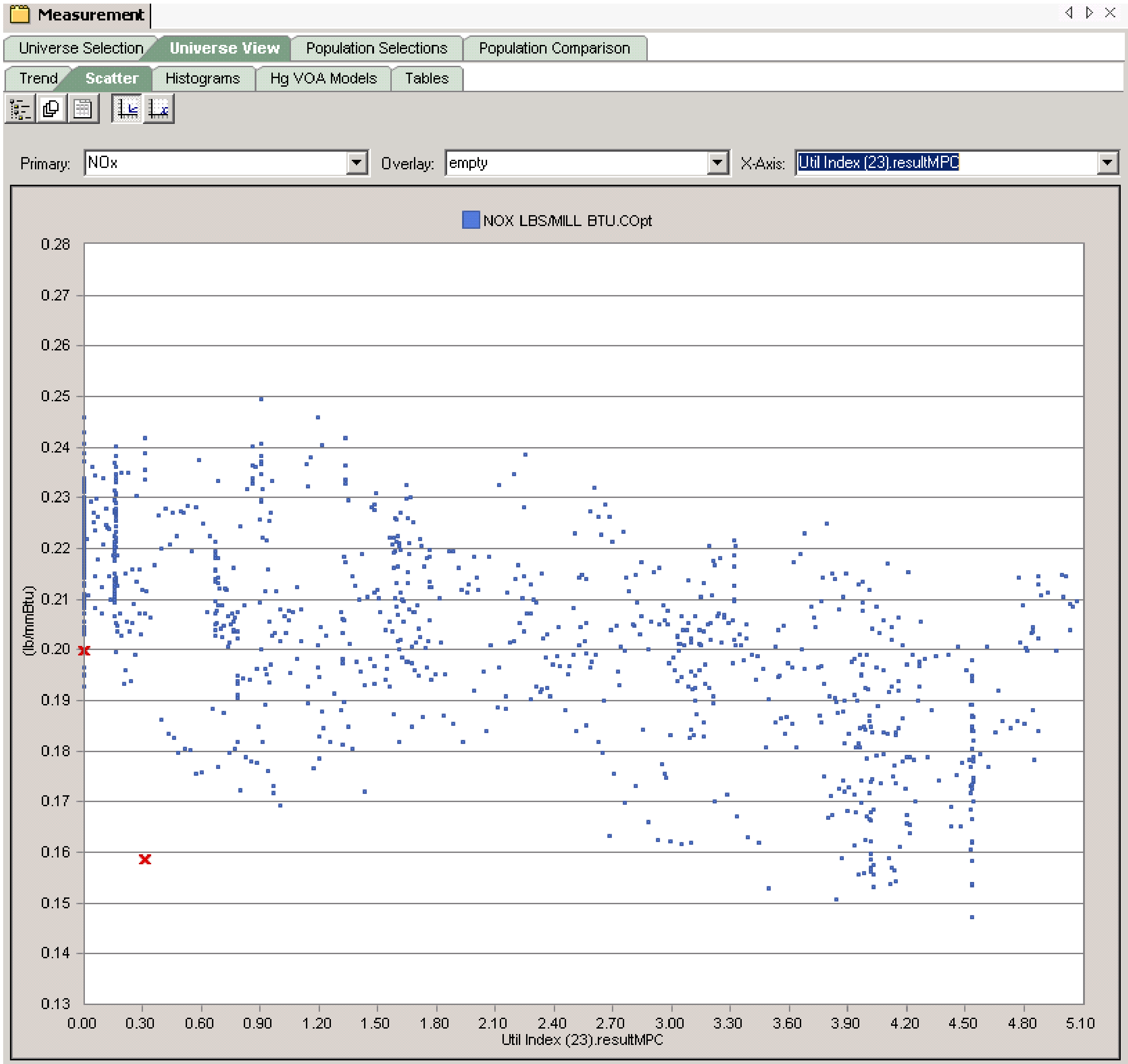

Figure 128: CEMS NOx vs. Util Index(23) MPC MVs enable result

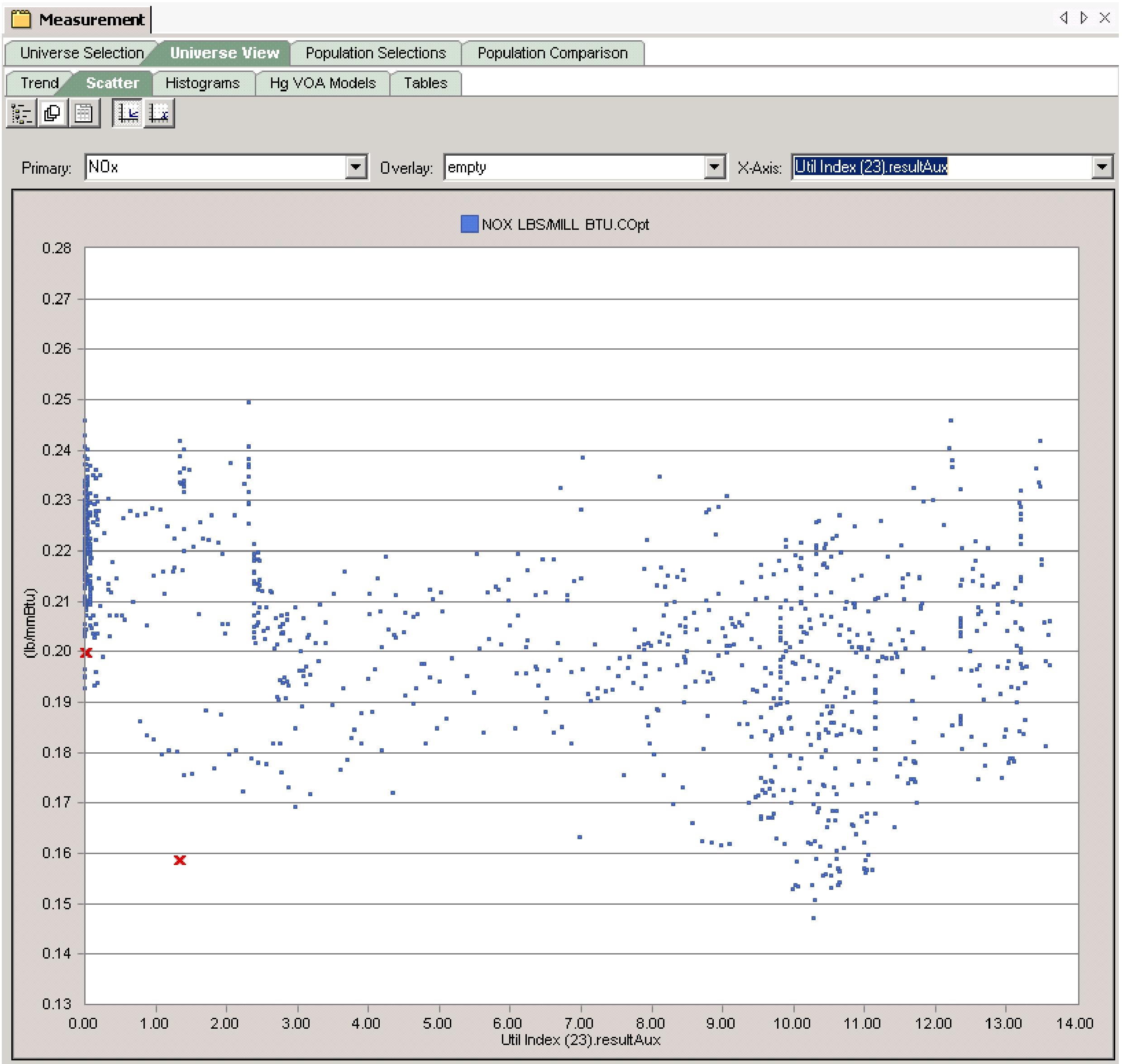

Figure 129: CEMS NOx vs. Util Index(23) Aux Air MVs enable result

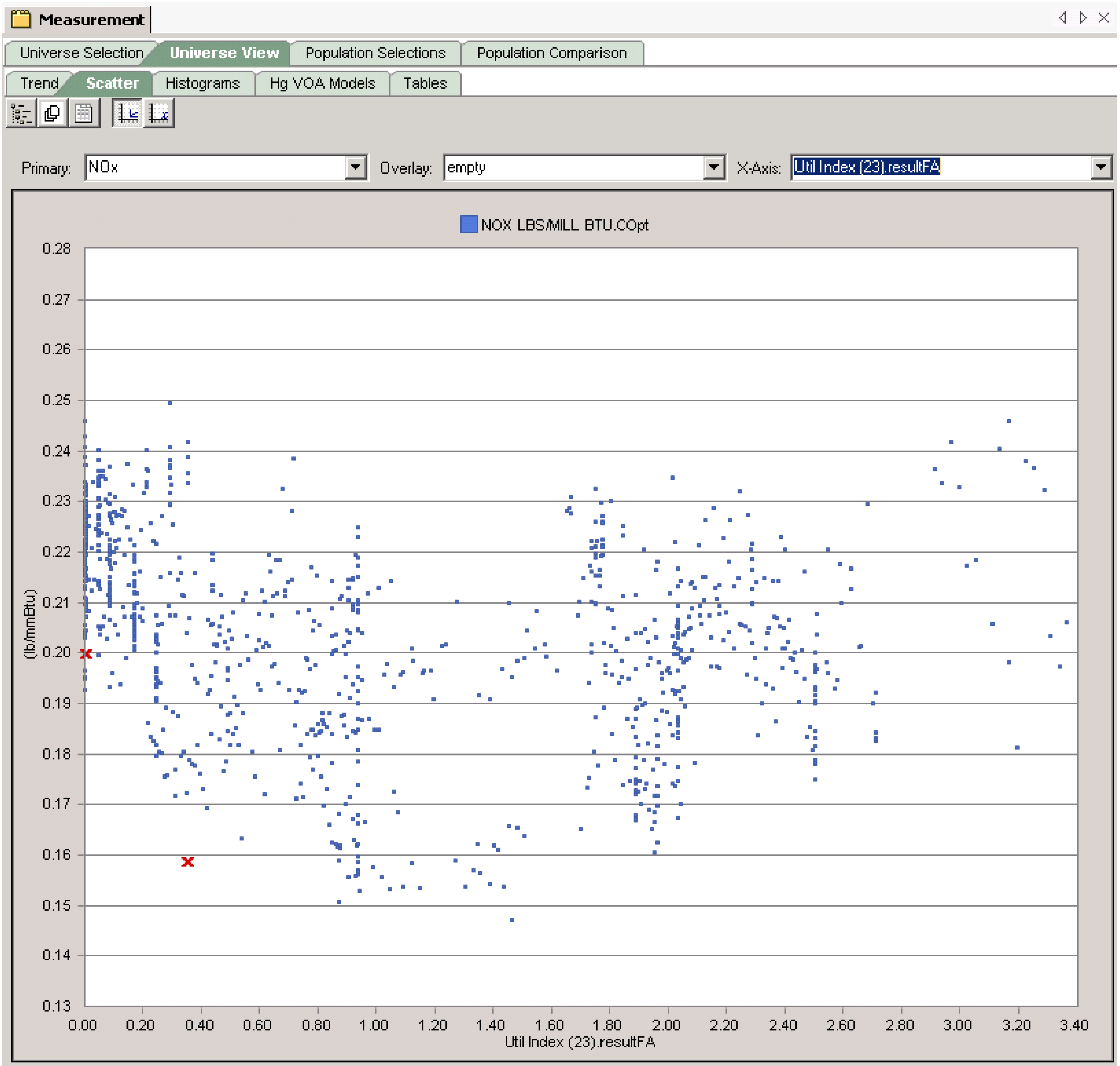

Figure 130: CEMS NOx vs. Util Index(23) Fuel Air enable result

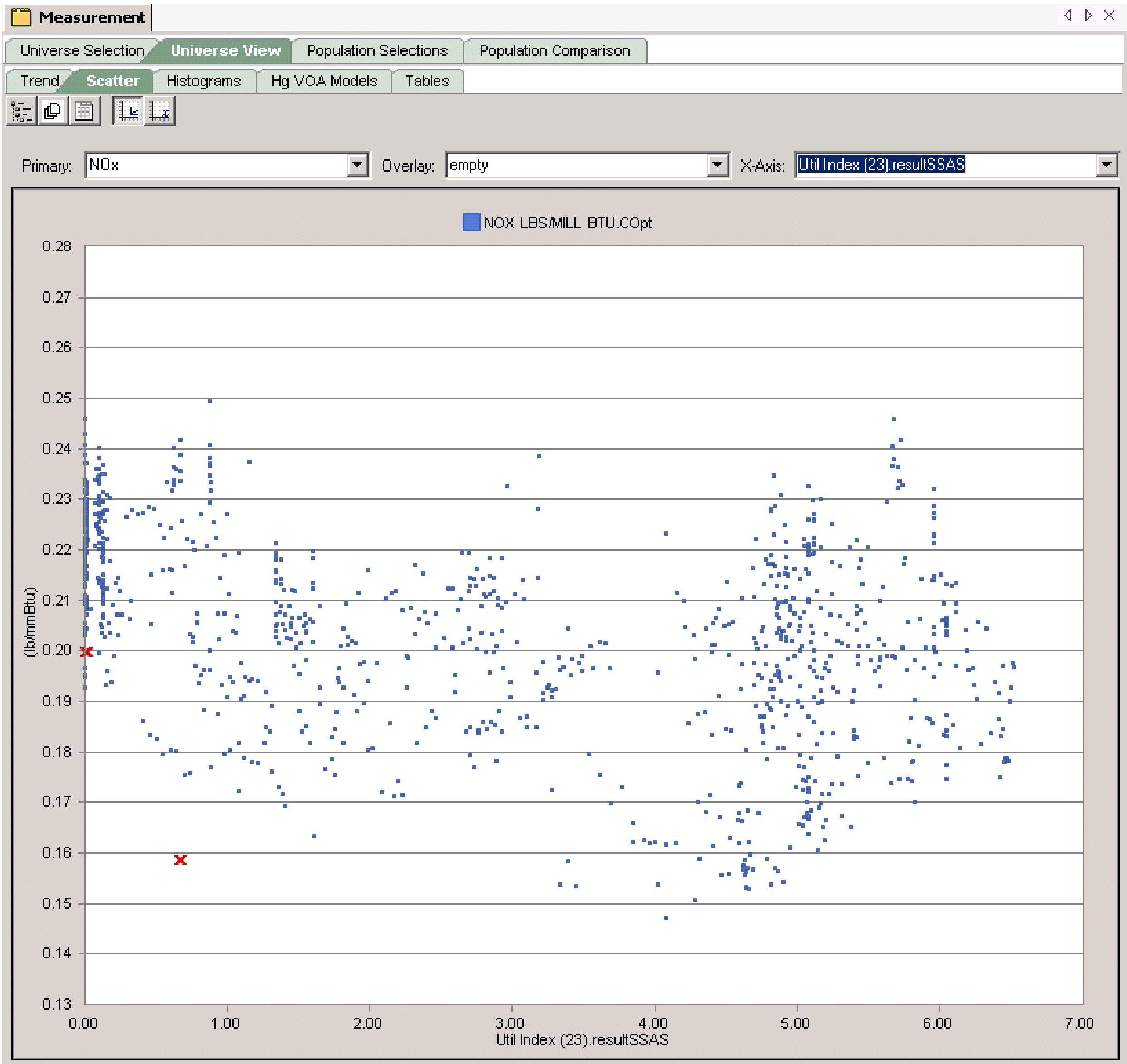

Figure 131: CEMS NOx vs. Util Index(23) SSAS (Overfire Air) enable result

3.6.4.4 Stack CO vs. Components of Utilization

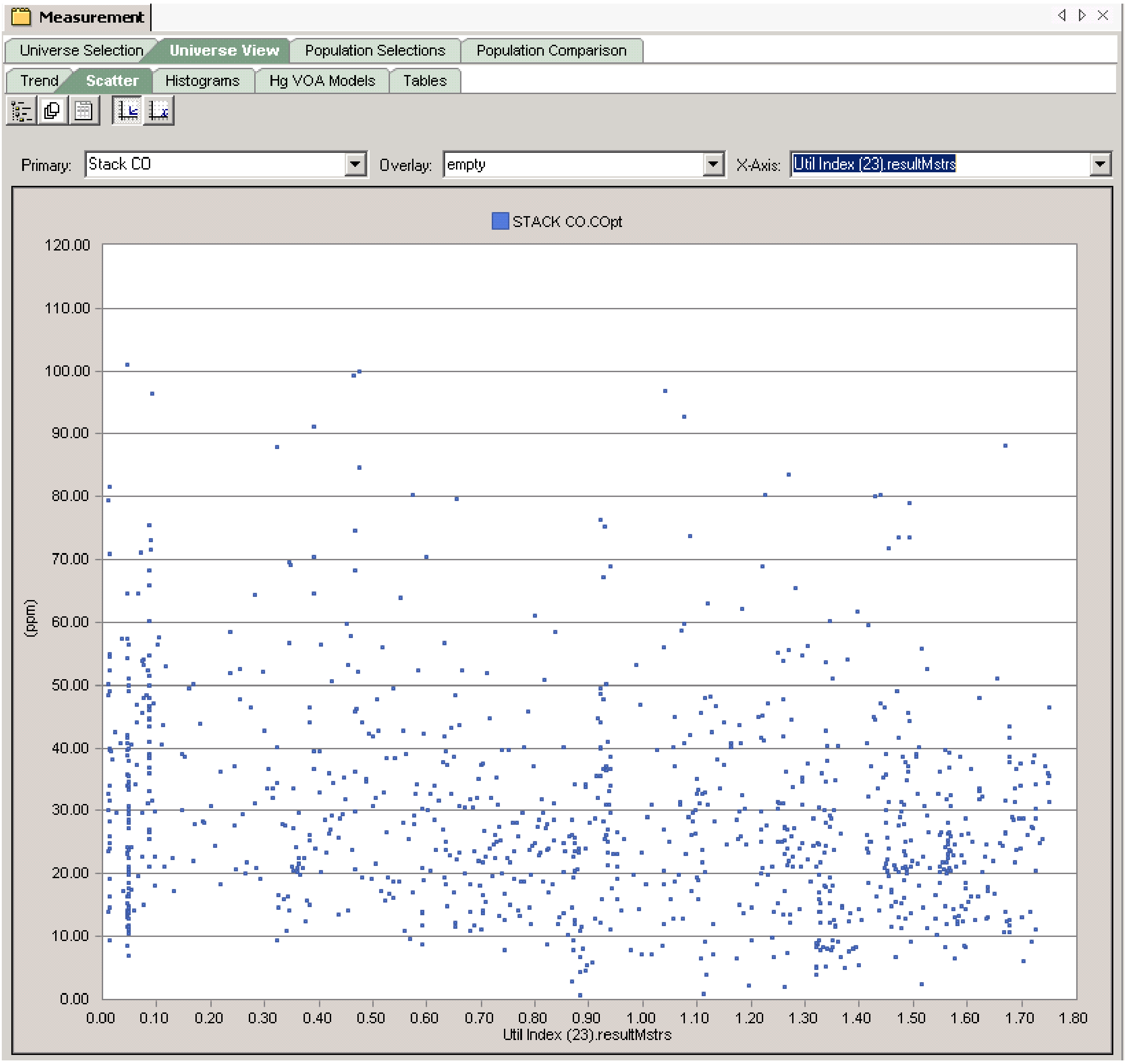

Figure 132: Stack CO vs. Util Index(23) Master enable result

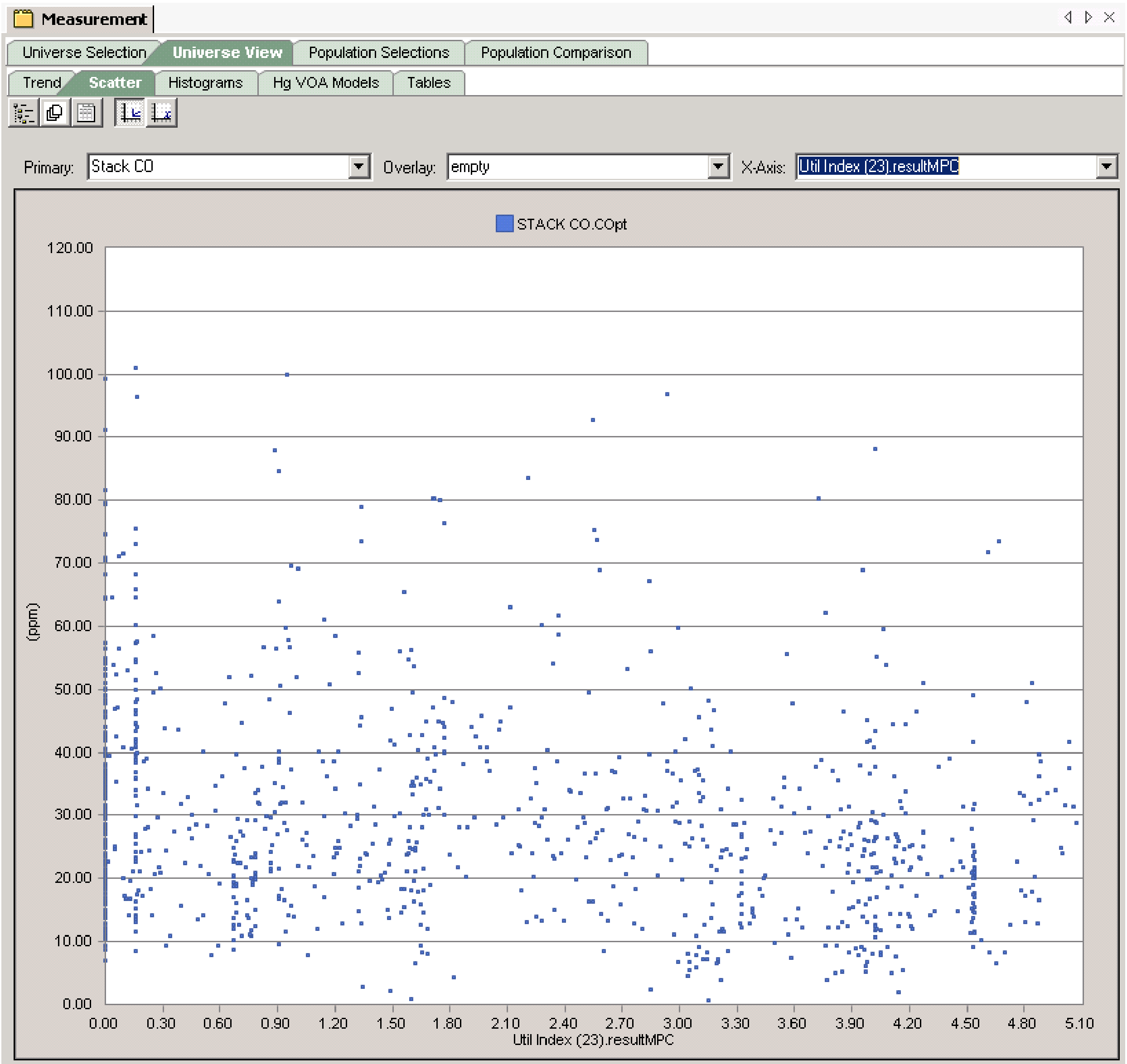

Figure 133: Stack CO vs. Util Index(23) MPC MVs enable result

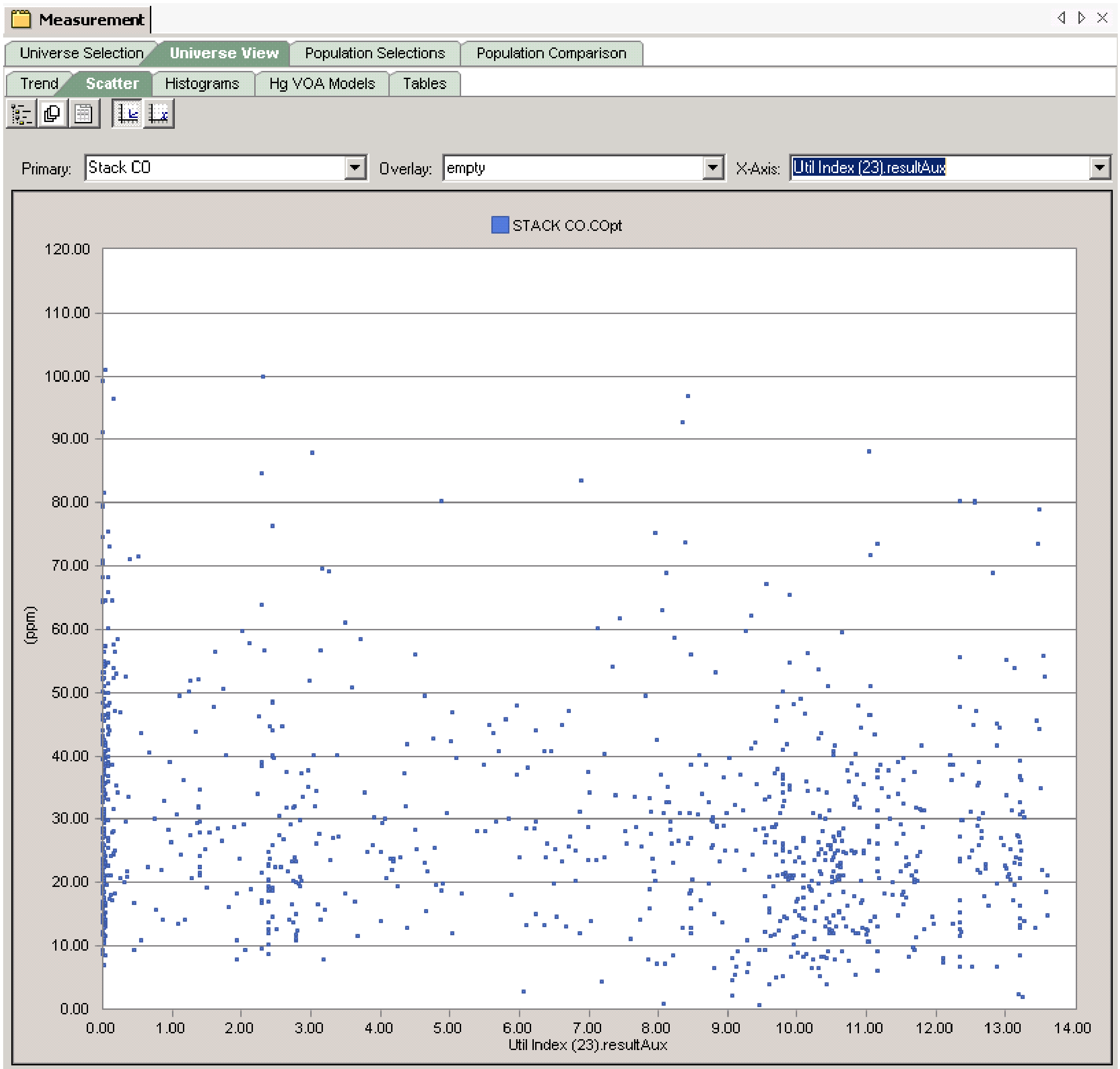

Figure 134: Stack CO vs. Util Index(23) Aux Air MVs enable result

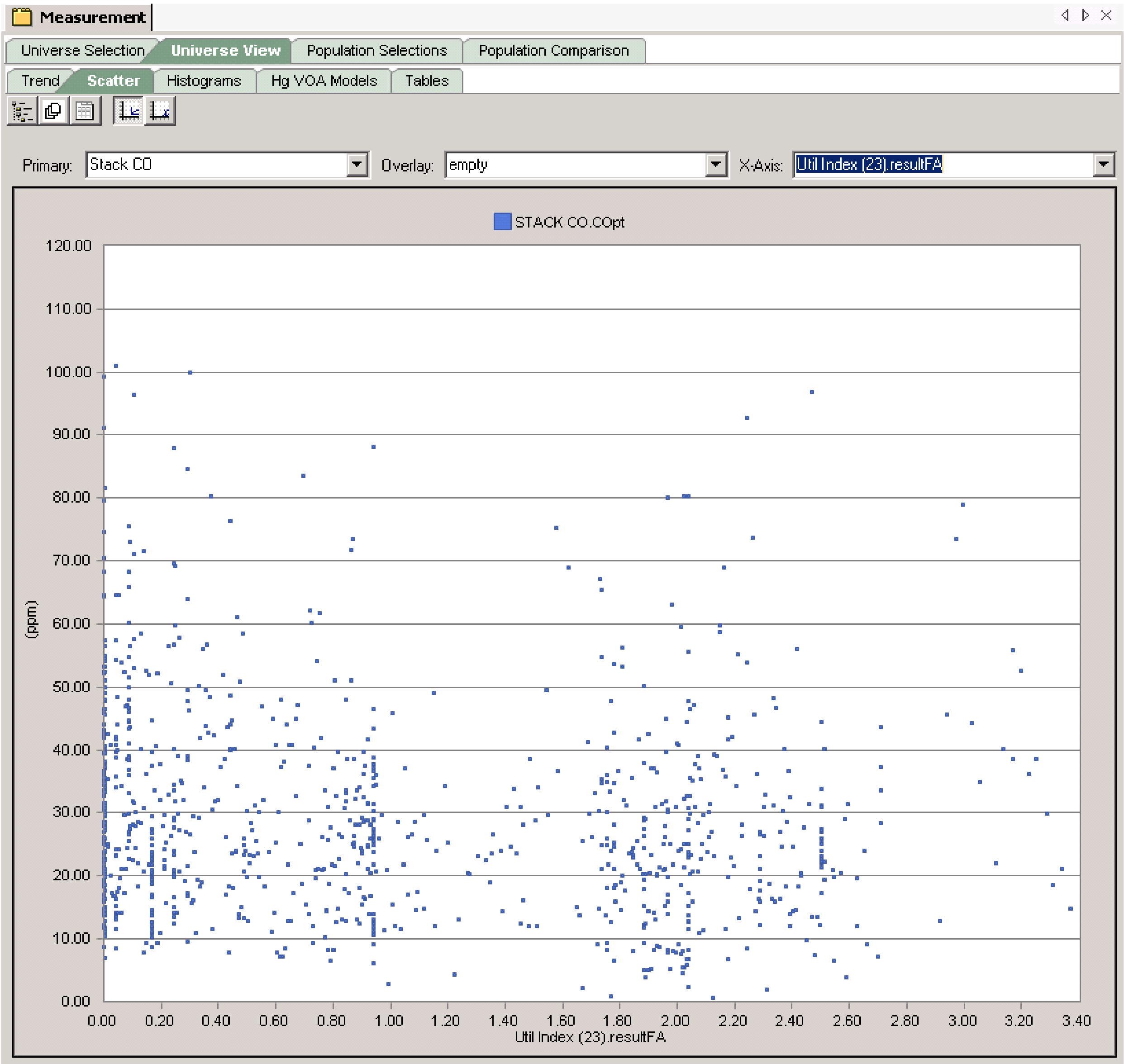

Figure 135: Stack CO vs. Util Index(23) Fuel Air MVs enable result

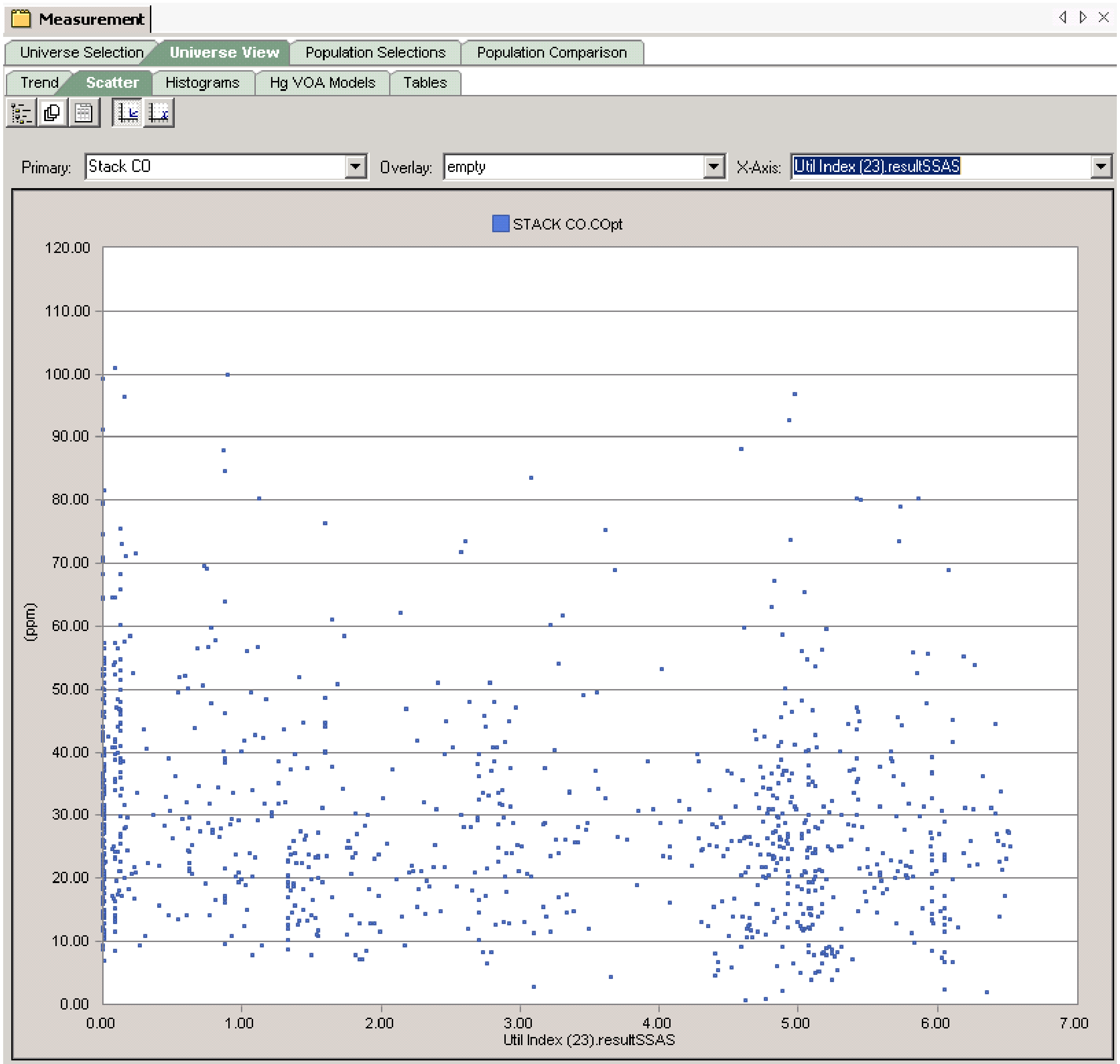

Figure 136: Stack CO vs. Util Index(23) SSAS (Overfire Air) MVs enable result

3.6.4.5 RH Temps vs. Components of Utilization

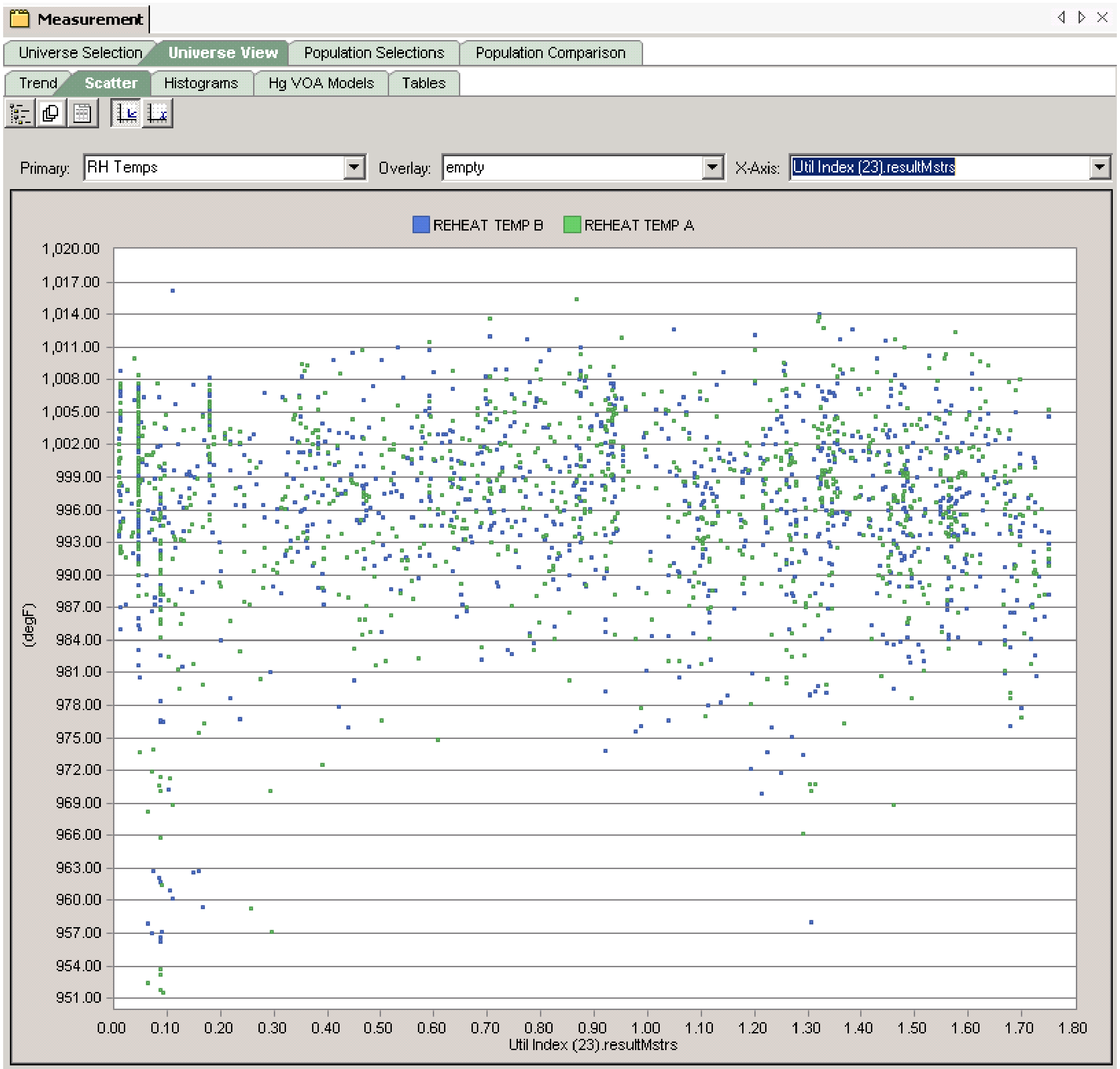

Figure 137: RH Temp A and B vs. Util Index(23) Master enable result

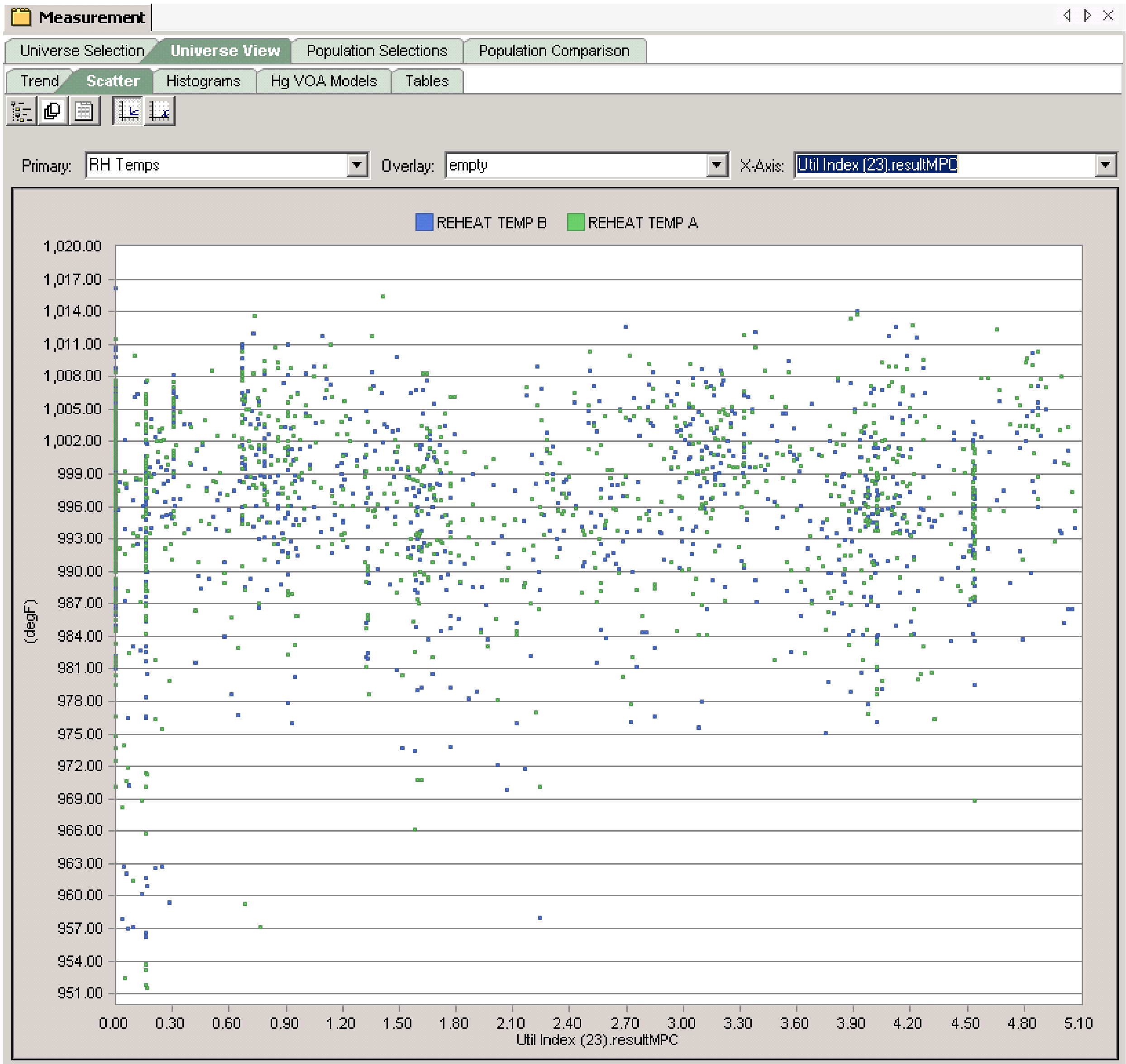

Figure 138: RH Temp A and B vs. Util Index(23) MPC enable result

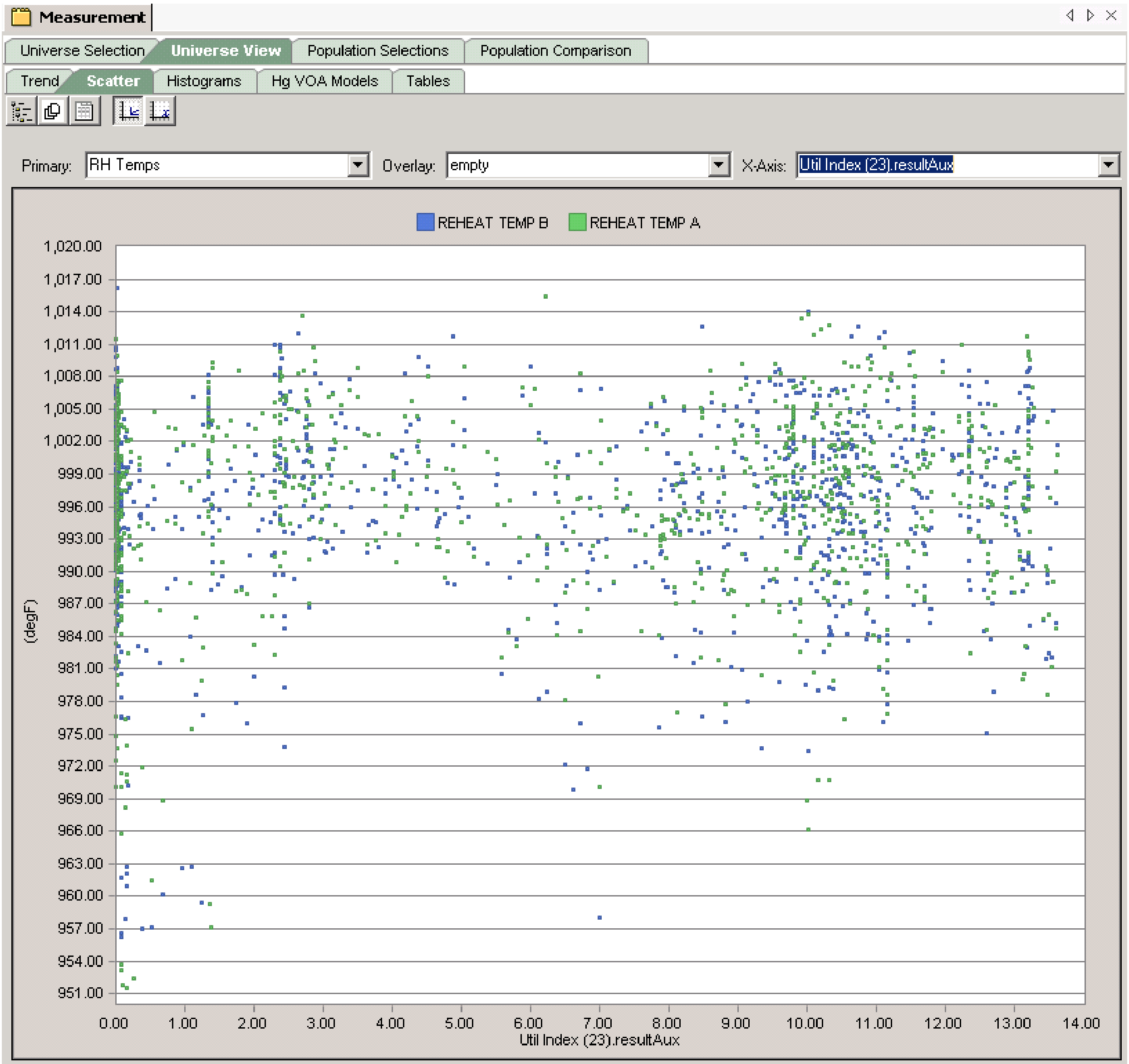

Figure 139: RH Temp A and B vs. Util Index(23) Aux Air MVs enable result

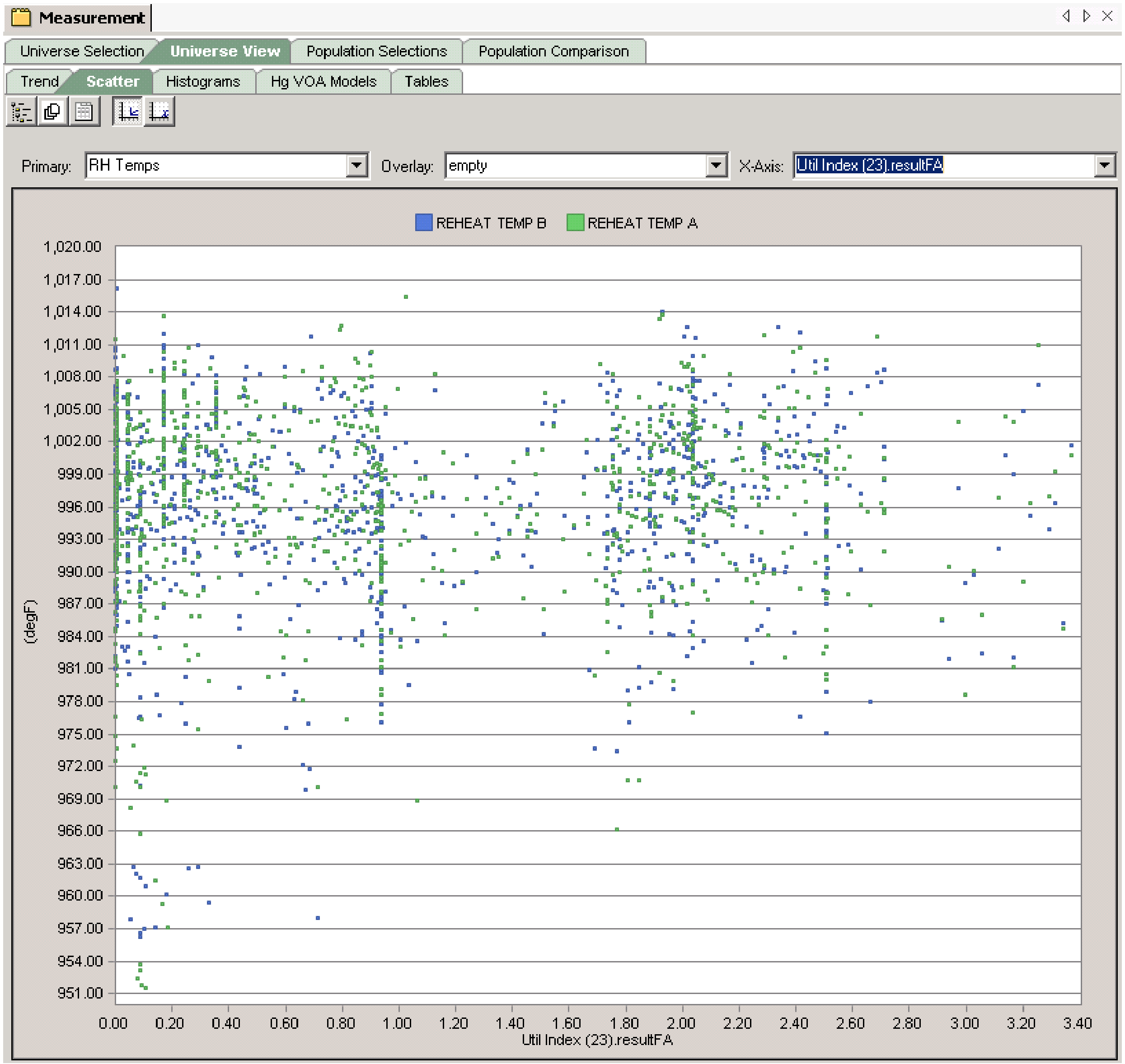

Figure 140: RH Temp A and B vs. Util Index(23) Fuel Air MVs enable result

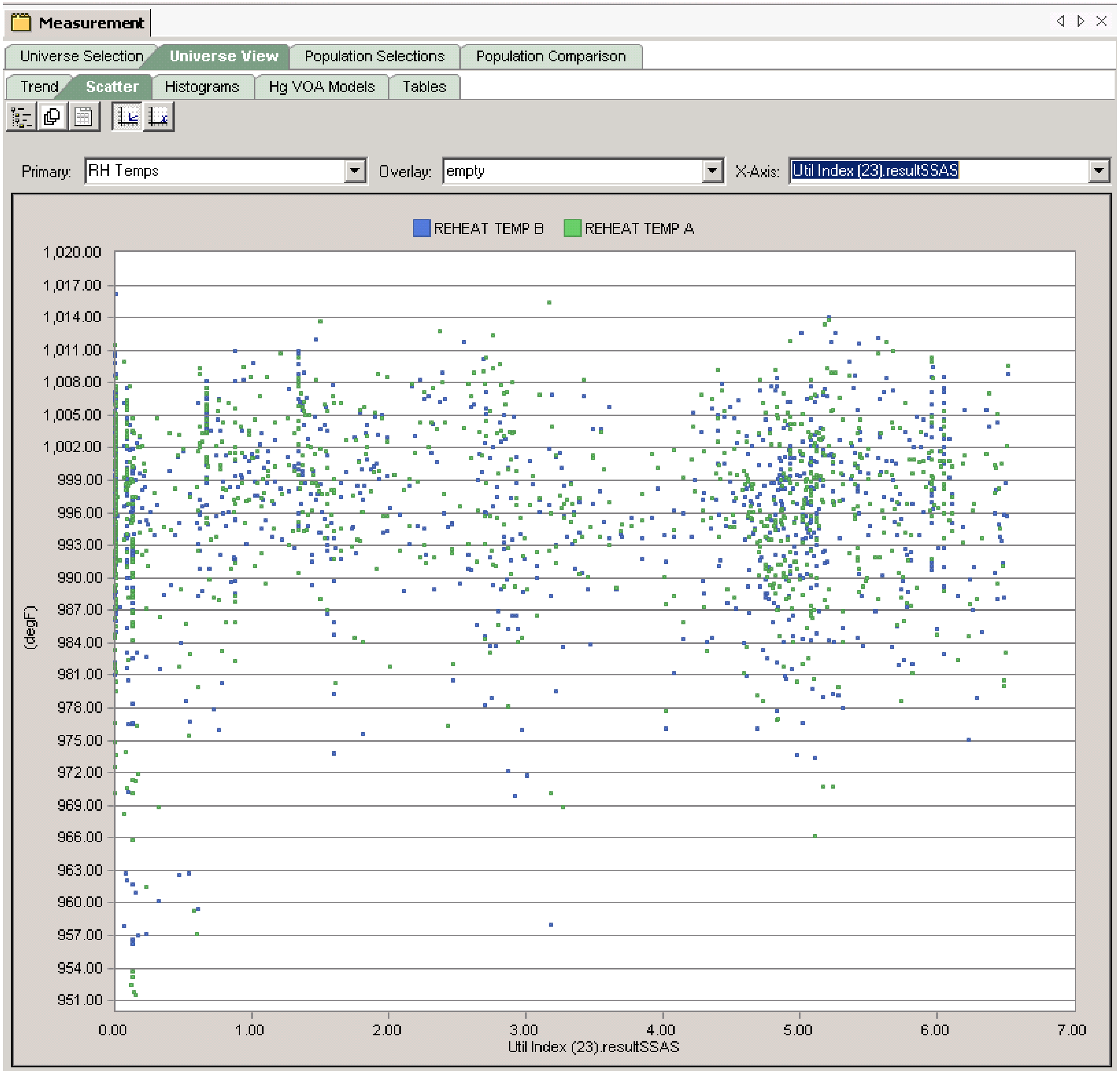

Figure 141: RH Temp A and B vs. Util Index(23) SSAS (Overfire Air) enable result

3.6.5 Long Term Comparison of Populations

This section compares two populations selected from recent data. One population was selected to represent the control or "OFF" case, where no optimization was applied. The other was selected to represent data where optimization was applied.

Fuel blend was not part of the selection criteria, and so was not held steady in each population. As such, the delta seen was expected to be attributable to the combined effects of fuel blend and optimization.

3.6.5.1 Data Selection

For the analysis shown, sampling was done at a frequency of 900 seconds for the whole Demonstration period (1/20/09 – 6/25/10). From this universe, data points where load was not above 880MW were excluded. These samples were then classified according to the following criteria:

- OFF (control population): CombustionOpt Master Enable OFF AND SootOpt Master Enable OFF.
- ON (experimental population): CombustionOpt Master Enable ON AND SootOpt Master Enable ON and both O2Trim and Burner Tilt MV (manipulated variable) Enables ON.

For the period analyzed, Heat Rate and Efficiency variables of useful quality were unavailable.

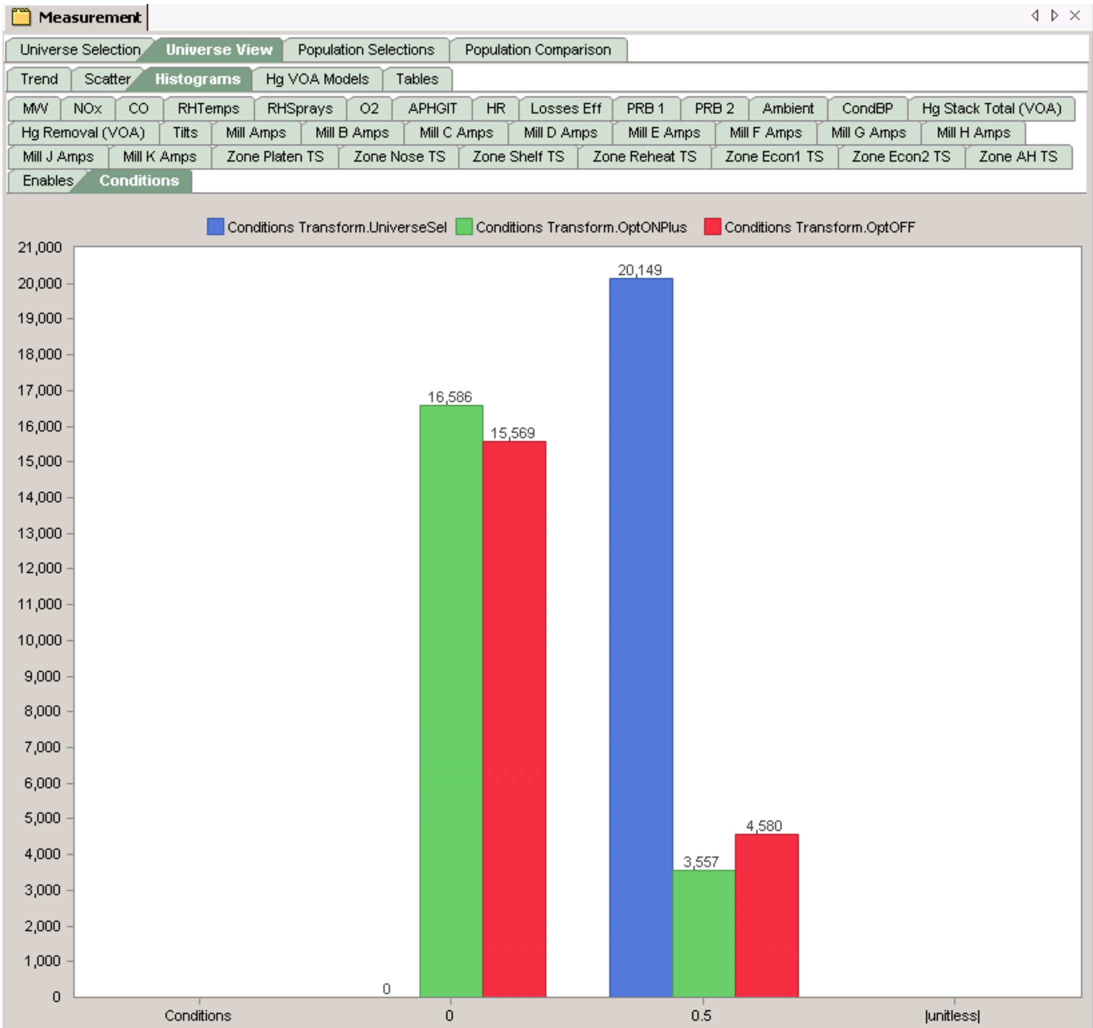

Figure 142: Experimental Data.
Green represents ON, Red represents OFF, 1 equals True and 0 equals False. Blue represents the count of samples considered for selection into ON, OFF, or neither population.

3.6.5.2 Tabulation of Long Term Population Means with Deltas

1/20/09 - 6/25/10, 900s, MW>880, ON Plus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
Hg Stack Total (VOA)	µg/m^3	6.07	5.58	-0.49	-8.1%	Down
Hg Removal	%	57.97	59.92	1.95	3.4%	Up

Table 10: Long Term Comparison of Population Means (Hg KPI's)

1/20/09 - 6/25/10, 900s, MW>880, ON Plus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
NOx	lb/MMBtu	0.212	0.189	-0.023	-10.8%	Down
CO	ppm	26.98	26.79	-0.19	-0.7%	< 40
RH Temp A	degF	993.3	994.76	1.46	0.1%	>980
RH Temp B	degF	989.03	992.84	3.81	0.4%	>980
O2 A	%	2.87	2.61	-0.26	-9.1%	>2
O2 B	%	2.52	2.47	-0.05	-2.0%	>2
Boiler O2	%	2.7	2.54	-0.16	-5.9%	>2
Tilt Dmd A	%	68.53	57.12	-11.41	-16.6%	Down
Tilt Dmd B	%	68.74	62.97	-5.77	-8.4%	Down
2A APH Gas Inlet	degF	775.4	770.66	-4.74	-0.6%	<780
2B APH Gas Inlet	degF	768.47	766.47	-2	-0.3%	<780

Table 11: Long Term Comparison of Population Means (non Hg KPI's)

1/20/09 - 6/25/10, 900s, MW>880, ON Plus O2 and Tilts					
Disturbance	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**
Load	MW	904.06	905.06	1	0.1%
Fuel Heating Value	Btu/lb	6905.75	6948.07	42.32	0.61%
PCT PRB	%	42.69	47.98	5.29	12.39%
Cond BP	inH2O	2.08	1.68	-0.4	-19.23%
Ambient	degF (wetbulb)	83.83	63.14	-20.69	-25%

Table 12: Long Term Comparison of Population Means (Disturbances)

With the exception of Losses Efficiency, Net Unit HR and Net Turbine HR (Corr) the values shown in the tabulation of means (Table 10 - Table 12) are essentially “measured values.” Some variables represent processed measured values, such as NOx, which is derived per CEMS standard model from NOx analyzer output in ppm.

Reheat Temperature, Boiler O2 and APH Gas Inlet Temperatures are considered as key performance indicators (KPI’s) because they do a good job of representing the thermal performance terms specific to the combustion and heat transfer process in the boiler, namely stack gas losses. In addition to being regulated emissions, CO and NOx represent the “quality” of combustion. Ideal combustion uses just enough O2 to burn out all available fuel and CO. Ideal low NOx combustion does this while creating the least amount of NOx possible. Unburned Fuel was not available for measurement directly. However it can be proxied by CO and is a significant input to thermal performance. Unburned Fuel also has implications for the sale-ability of fly ash.

Tilts are shown because tilt operating position, in addition to affecting combustion and heat transfer, does a good job of representing the degree to which the unit is kept in “control range” with respect to both combustion and heat transfer processes. Tilts that are either too low or too high prevent the unit from responding to steam temperature excursions in one direction or the other, and as such represent non-ideal conditions. Typically very low or very high tilt position can also lead to other problems such as high Super Heat tube metal temperatures or slagging conditions. Slagging conditions are caused by, among other things, temperatures that exceed the ash fusion temperature in the presence of surfaces where the ash can “stick”. APH Gas Inlet Temperature, in addition to its role in representing total thermal efficiency, represents the degree to which operation is kept under control. Very high back-end temperatures (as high as those seen on this unit) can affect APH longevity. Other reasons to consider back-end temperatures include SCR performance, for units equipped with those.

This list of KPI’s is not generally comprehensive, but it is fairly complete for LMS U2. Each unit pushes against the common physical constraints of combustion and heat transfer processes in different ways, due to different specific characteristics of each boiler.

For instance LMS U2 does not use SH or RH sprays. These are key KPI’s that would be shown for most units. The list of variables in Table 10 and Table 11 represents benefits in a holistic way for LMS U2, given the processes being addressed and the instrumentation available.

Table 12 shows the means for the major disturbances that could affect the experiment. As shown, Load is a non-issue. Fuel heating value represented a fairly small difference and was suspect anyway due to drift over time in the Sabia analyzer (both values were excessively low for the blend indicated). Differences in blend, at least when looking at the mean, represented possibly significant causal disturbances in the Hg and NOx dimensions. That said, the mean values for fuel blend appear to be affected by outlier distribution. Because of the way these signals have to be cleaned to remove sections where neither conveyor was running and that cause the blend to read zero, these outliers are difficult to remove. The visual plots suggest, contrary to the mean, that the average blend was somewhat lower in the ON data. This would bias Hg Removal down, Mercury Stack Total up, and NOx up in the ON data, meaning that the actual improvements shown in the ON data, if normalized for fuel blend, would be more favorable than they appear.

Though differences in ambient conditions and condenser back pressure exist, their effect would primarily show up in Heat Rate and Efficiency, variables that were not available for this analysis and are not shown.

3.6.5.2.1 Comments on Disturbances

Unit load is the single largest driver of boiler performance across multiple dimensions and if not normalized in both populations, would represent a significant disturbance factor. The purpose of focusing the comparison on populations already selected for a specific MW range is to neutralize this factor.

Fuel Heating Value, or the "hotness," is known to affect both the combustion and heat transfer process in a sometimes subtle way but across many different dimensions. In the case of LMS U2, which blends PRB and Lignite fuels, disturbances from this variable can be expected to be felt in the Heat Rate, NOx and mercury dimensions. This is because PRB fuel has a heating value near 8,200 Btu/lb as well as lower nitrogen and mercury content than Lignite fuel.

Percent PRB represents the ratio of PRB to Lignite being shipped to the unit's coal silos on the delivery conveyor belts. This value is to some degree redundant with the Fuel Heating Value signals. It is helpful exactly for this reason, and also because some variability exists in the BTU content of both fuels. Like Fuel Heating Value, disturbances from this variable can be expected to be felt in the Heat Rate, NOx and Mercury dimensions. Higher fuel blend indicates more PRB, which means less incoming mercury, and nitrogen and more Btus per pound of fuel.

Condenser Back Pressure represents the "heat sink" conditions at the "bottom" (high entropy, low temperature) of the thermal cycle. Lower values represent higher vacuum, indicating the condenser represents a "deeper" heat sink, and is therefore better able to reject waste heat (unusable energy) to the outside environment. This in turn makes the cycle more efficient. This value can be affected by condenser cleanliness as well as ambient conditions. Disturbances here affect primarily Net Unit Heat Rate. Net Turbine Heat Rate (Corrected) is designed to represent performance against a normalized design condition.

Ambient Temperature and Humidity (Wet Bulb Temp) is to some degree redundant with Condenser Back Pressure. In fact the difference in Condenser Back Pressure seen in Table 12 is most likely attributable to differences in this variable. Ambient temperature can to some degree affect a variety of variables including Stack Losses, and back end temperatures (APH Gas Inlet) in both positive and negative ways. Mostly in the mean, this variable provides an indication of the skew of the data in time.

3.6.5.3 Population Comparison Plots

The plots and tables shown in the following pages (175- 203) compare populations of data where optimization was active to populations where it was not. OFF, or control data, is always on the left in the figure; ON, or experiment data, is always on the right in the figure as indicated in Figure 143. Plots include histograms, data series plots (non-continuous time series), which show the relative distribution of values for the variable in question, and scatter plots vs. Load.

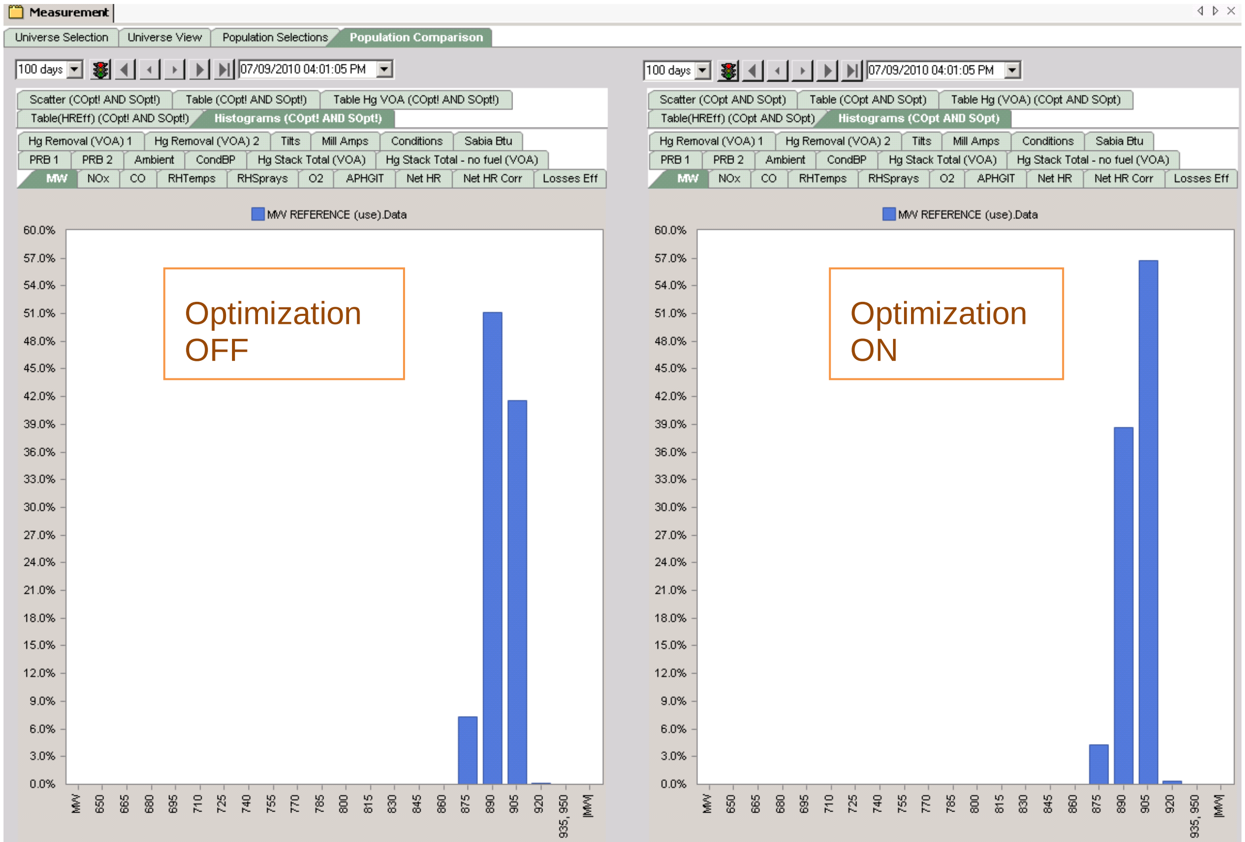

Figure 143: Comparison Plots

3.6.5.4 Mercury

3.6.5.4.1 Mercury Removal (VOA)

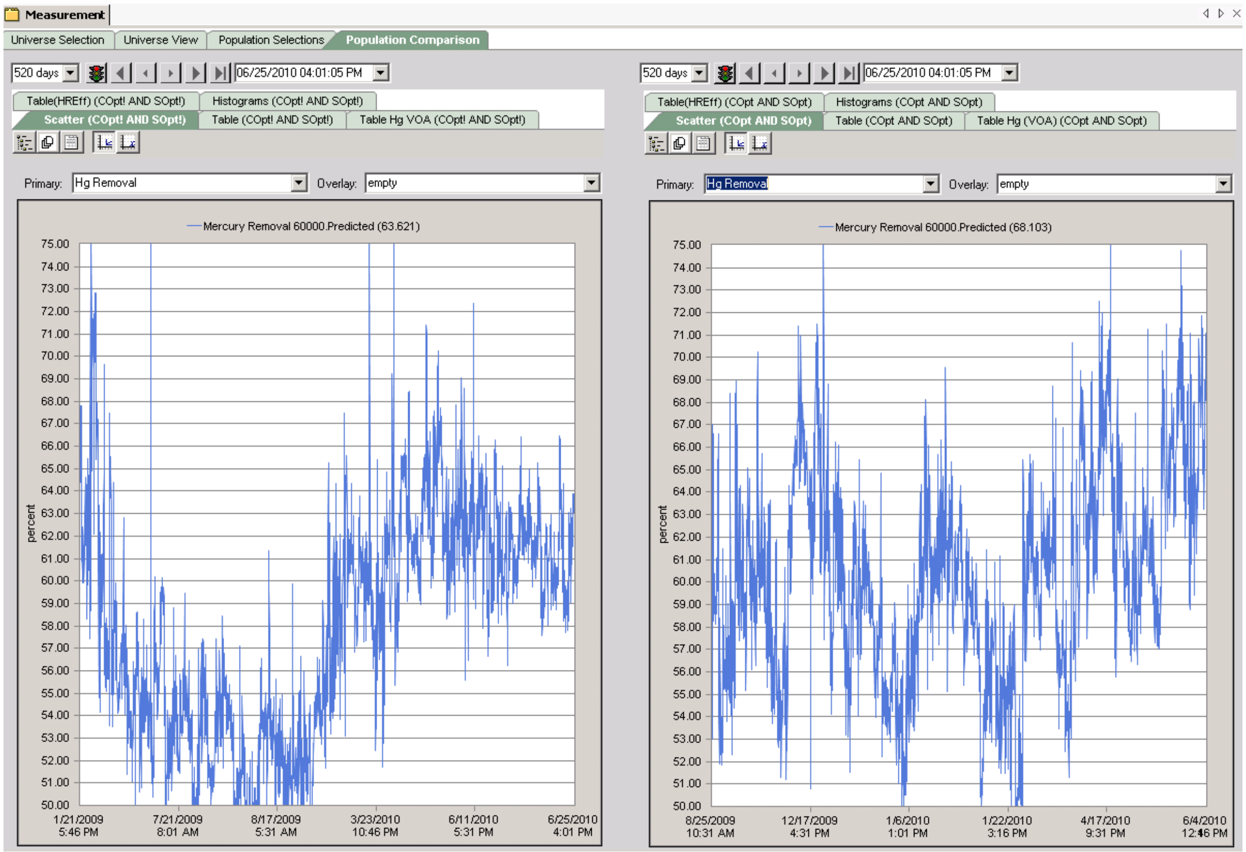

Figure 144: VOA Predicted Mercury Removal OFF(Left) vs. ON(Right) populations

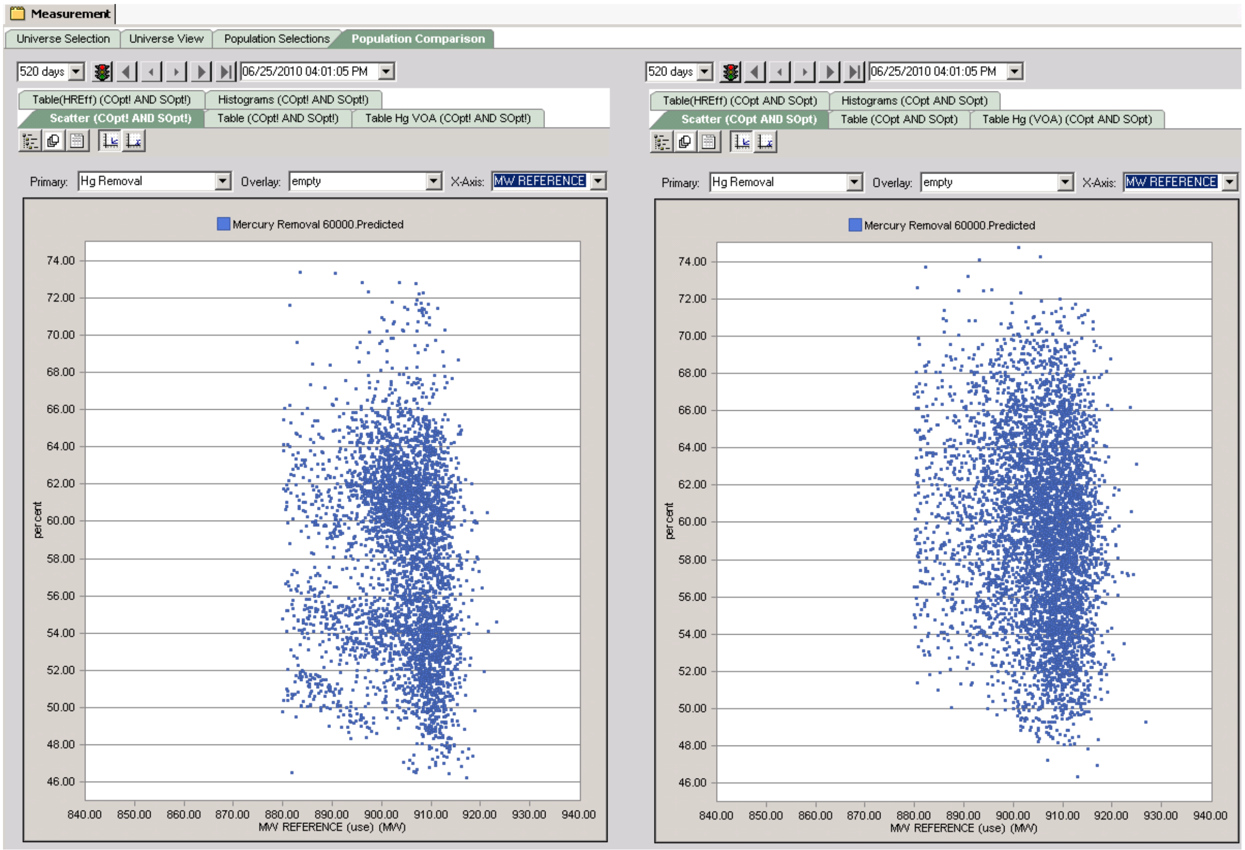

Figure 145: VOA Predicted Mercury Removal OFF(Left) vs. ON(Right) populations

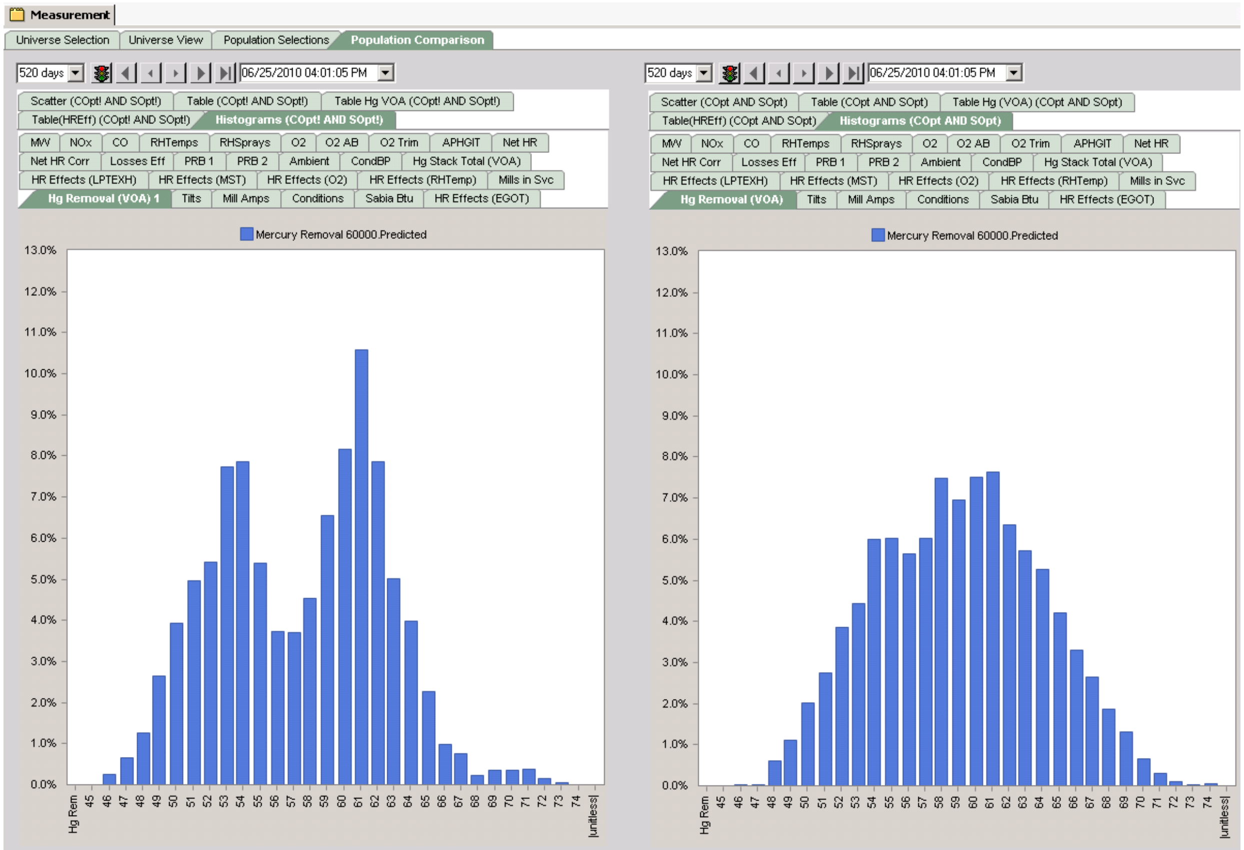

Figure 146: VOA Predicted Mercury Removal OFF(Left) vs. ON(Right) populations

3.6.5.4.2 *Mercury Stack Total (VOA)*

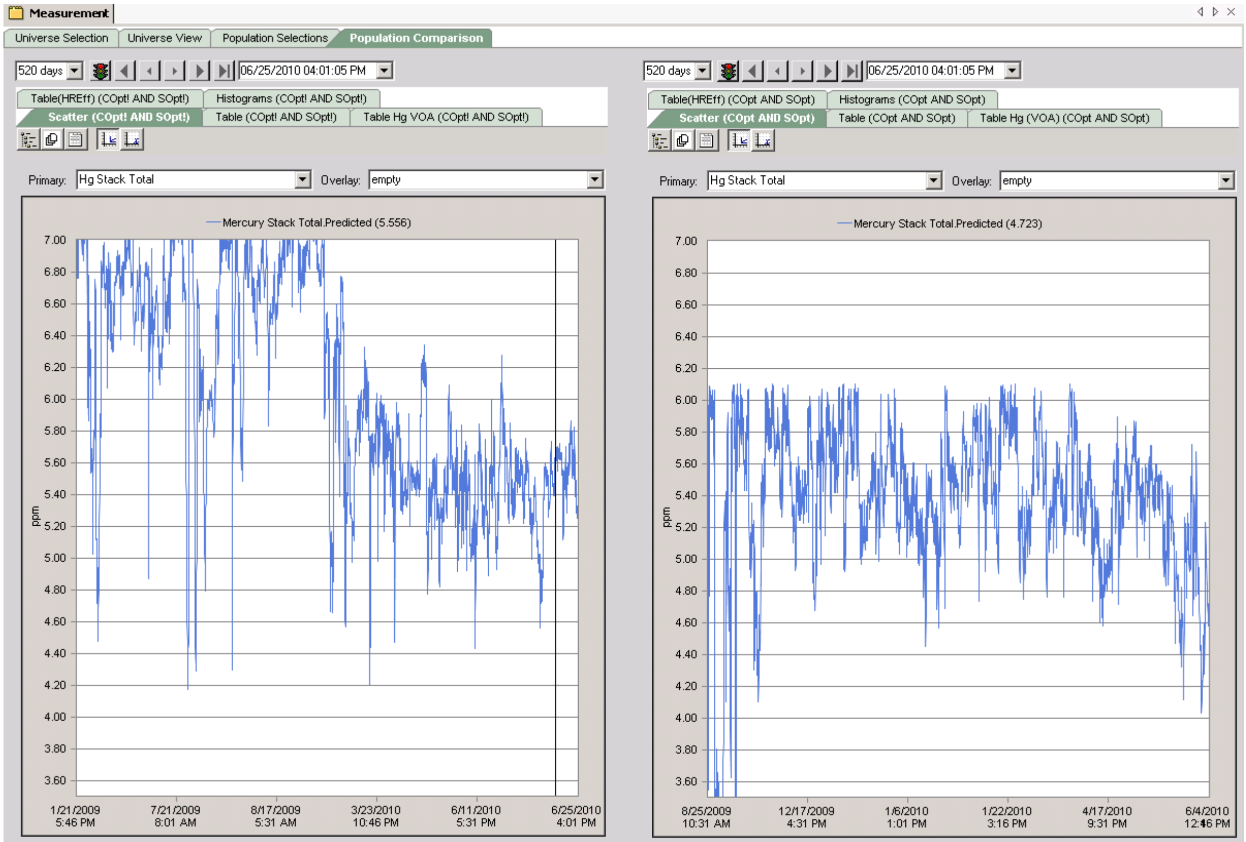

Figure 147: VOA Predicted Mercury Stack Total OFF(Left) vs. ON(Right) populations

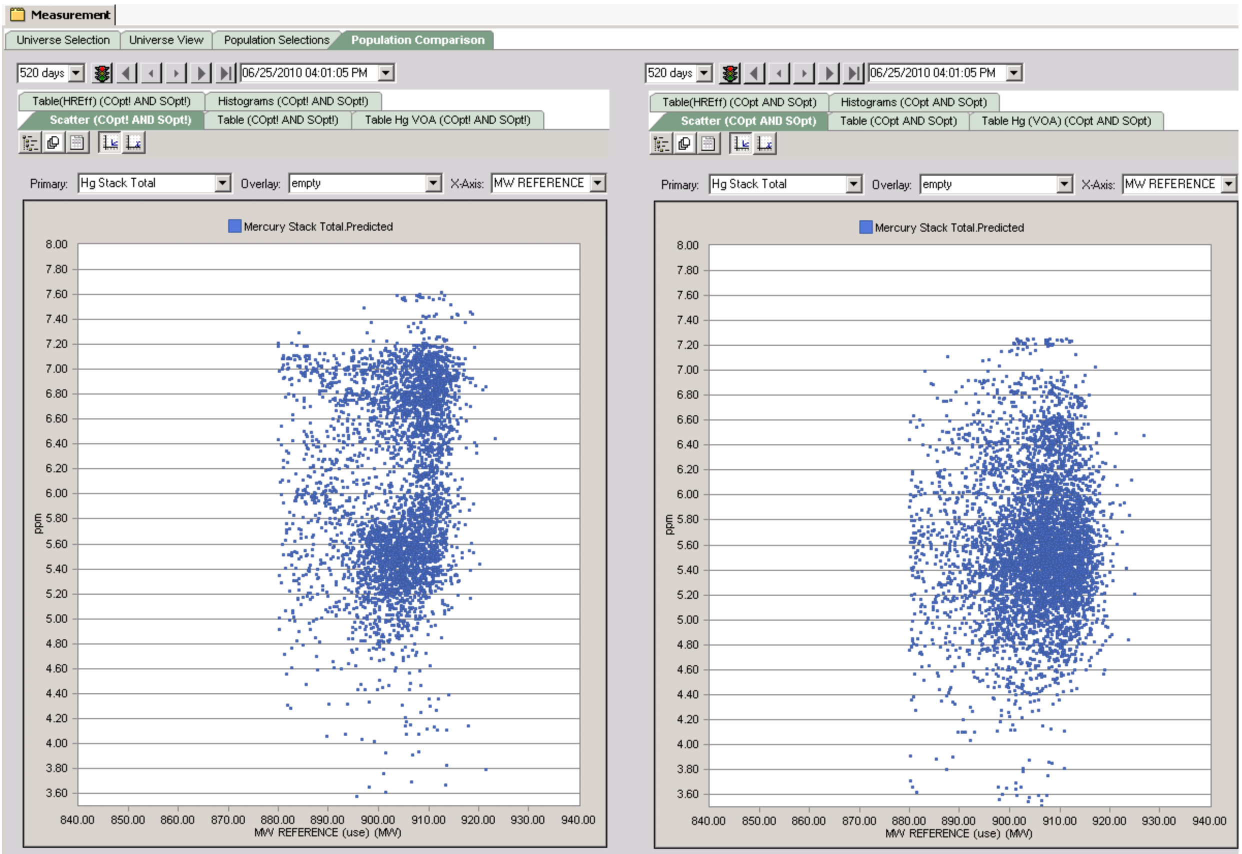

Figure 148: VOA Predicted Mercury Stack Total OFF(Left) vs. ON(Right) populations

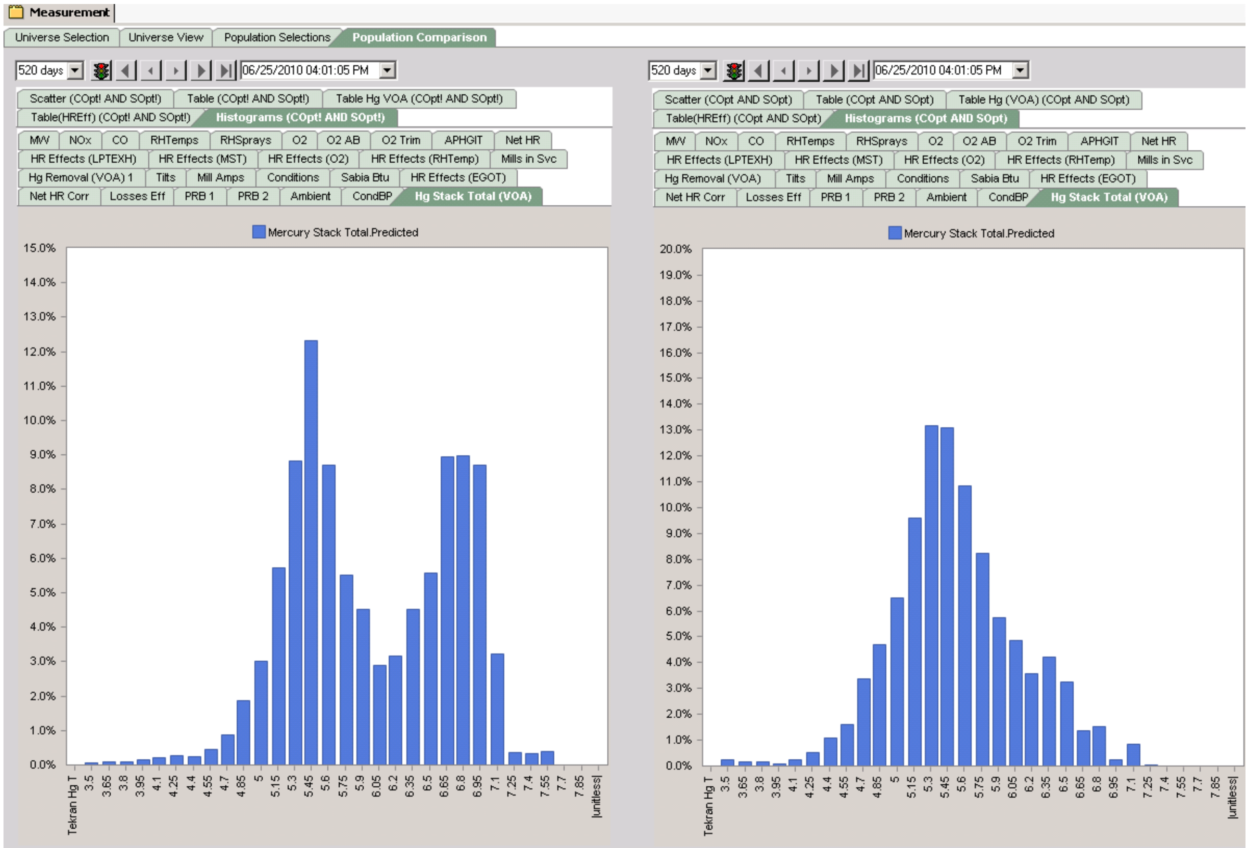

Figure 149: VOA Predicted Mercury Stack Total OFF(Left) vs. ON(Right) populations

3.6.5.5 CEMS NOx

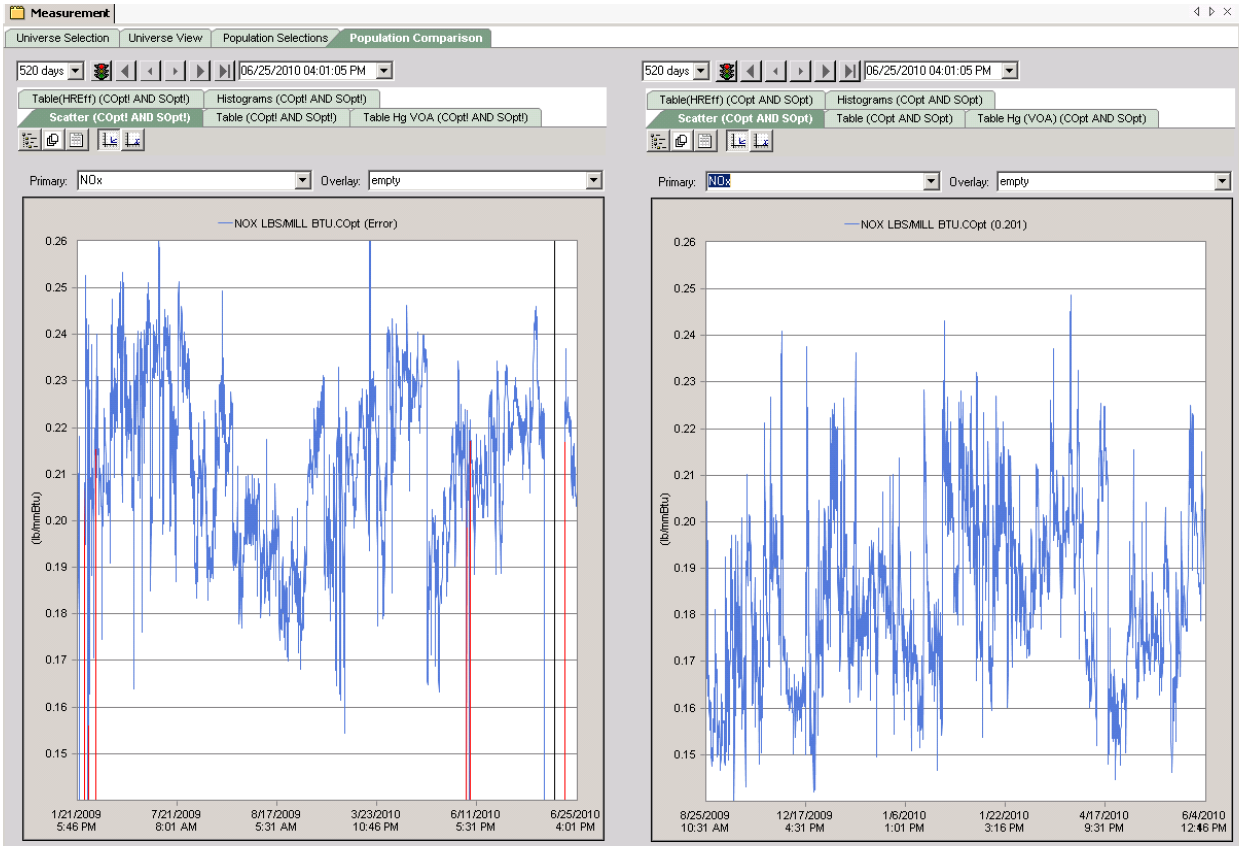

Figure 150: CEMS NOx OFF(Left) vs. ON(Right) populations

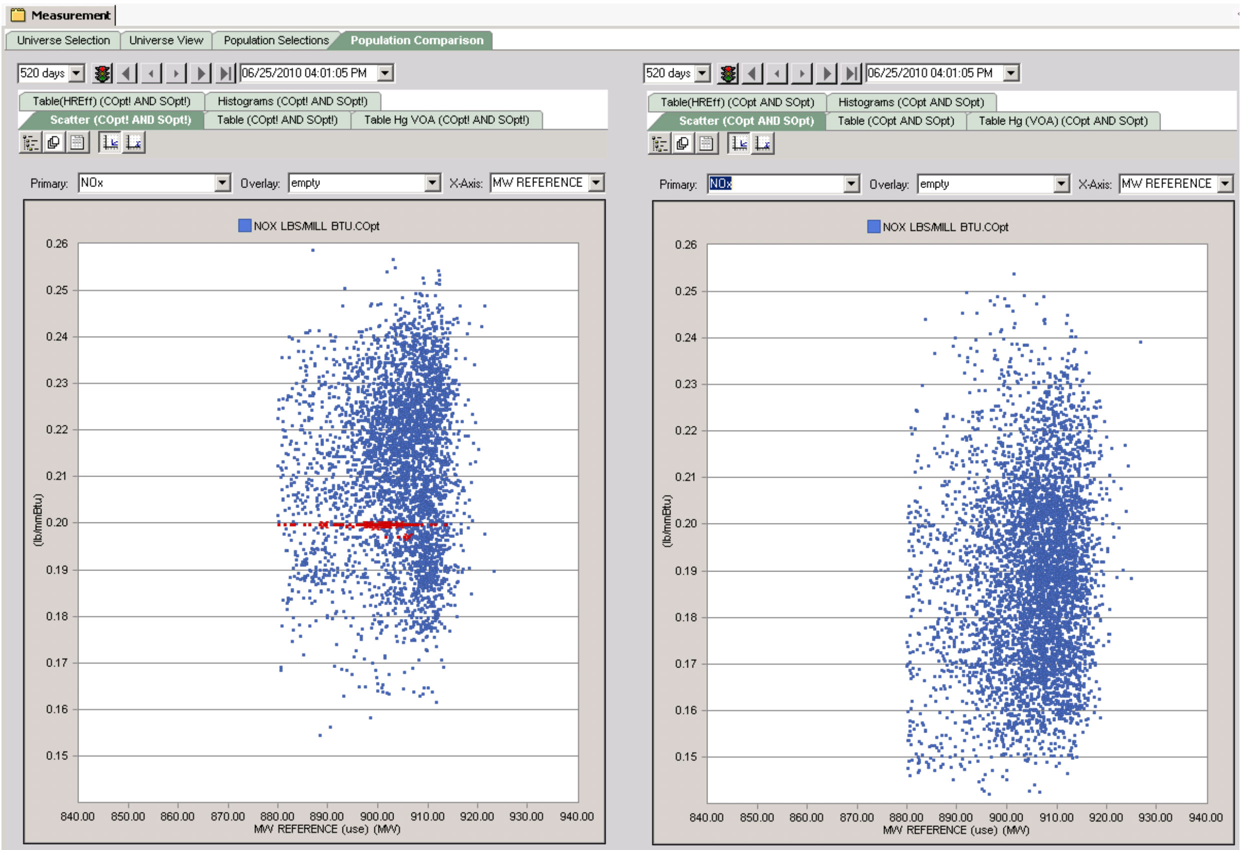

Figure 151: CEMS NOx OFF(Left) vs. ON(Right) populations

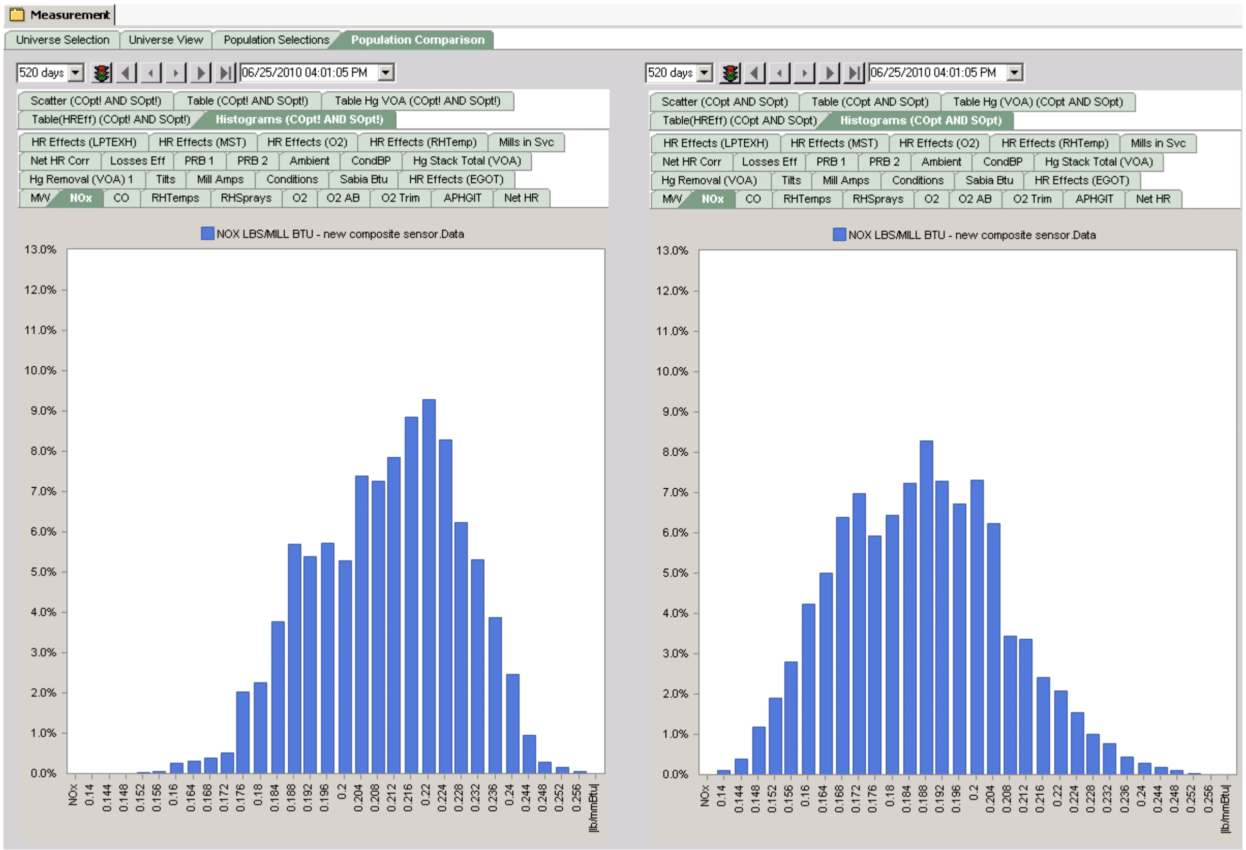

Figure 152: CEMS NOx OFF(Left) vs. ON(Right) populations

3.6.5.6 Stack CO

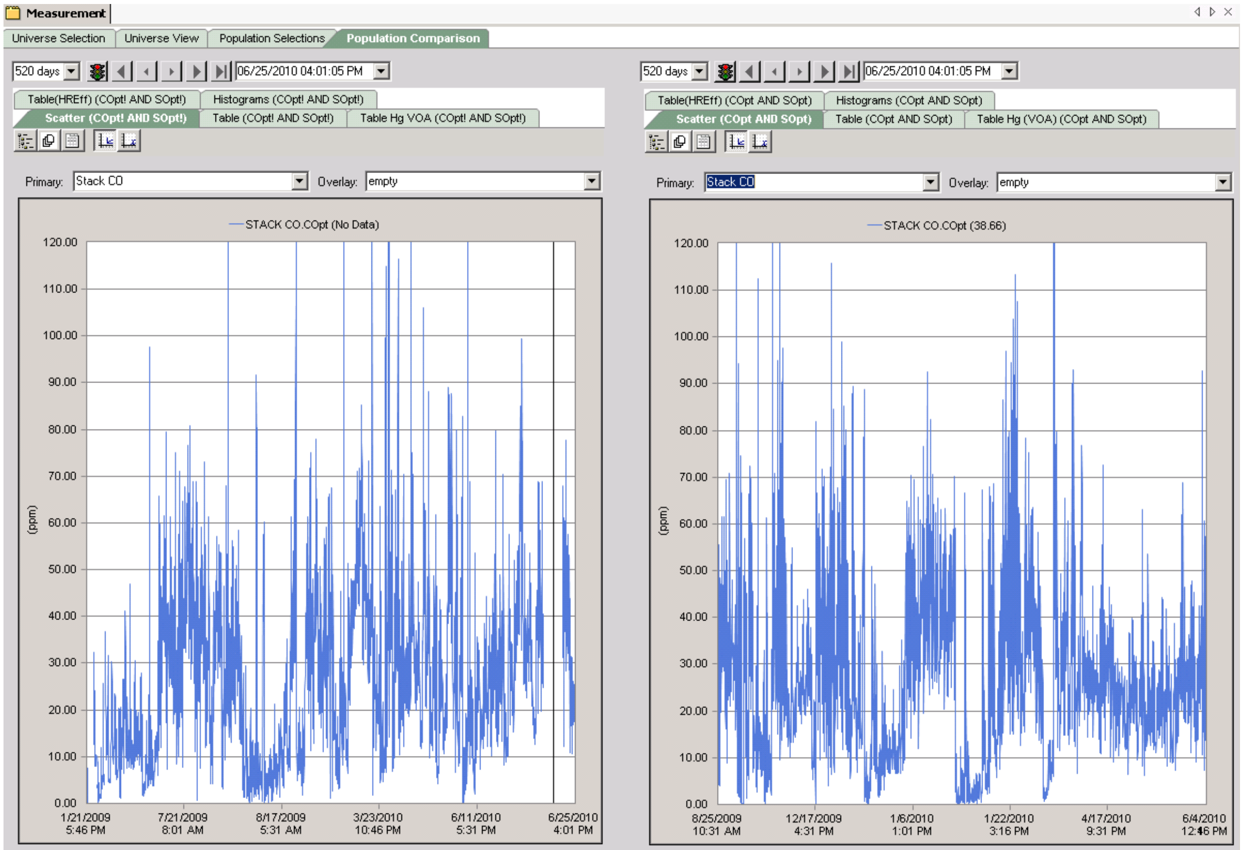

Figure 153: Stack CO OFF(Left) vs. ON(Right) populations

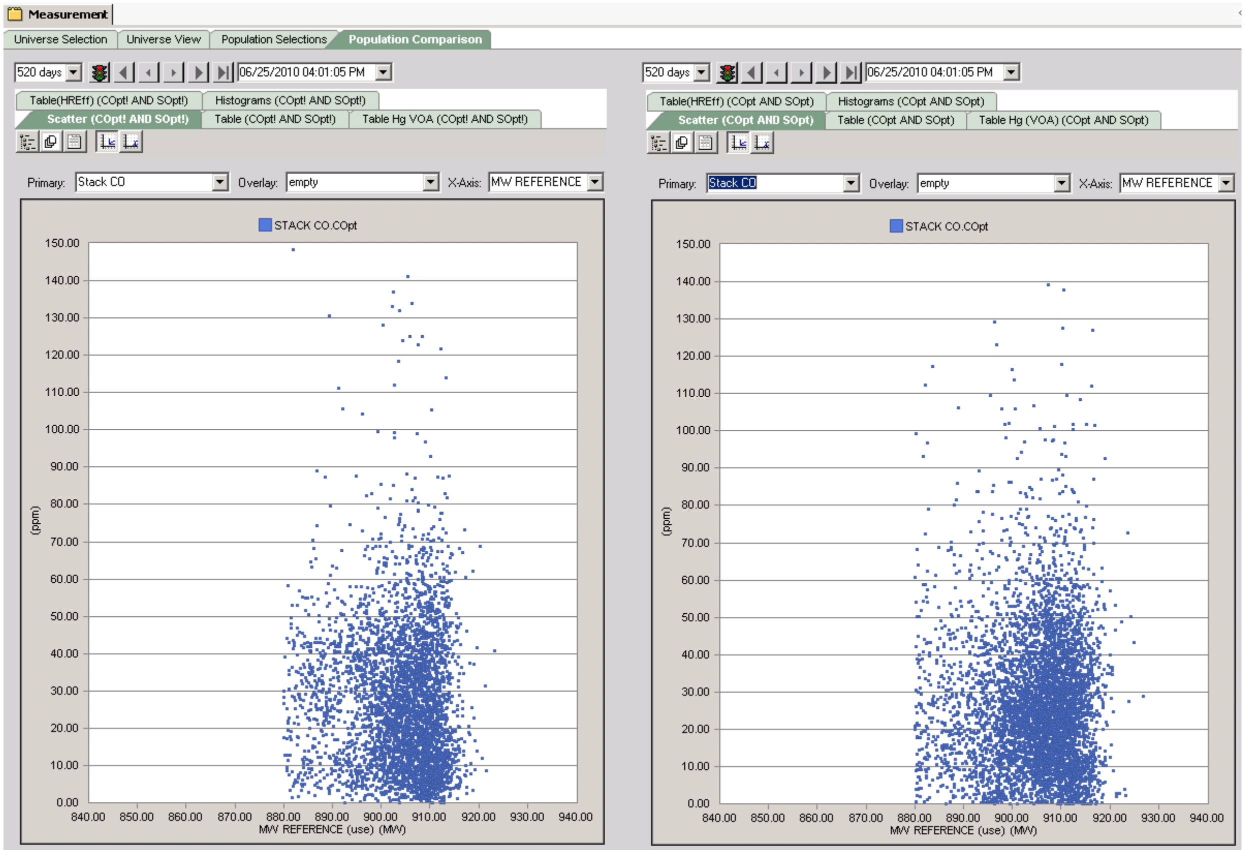

Figure 154: Stack CO OFF(Left) vs. ON(Right) populations

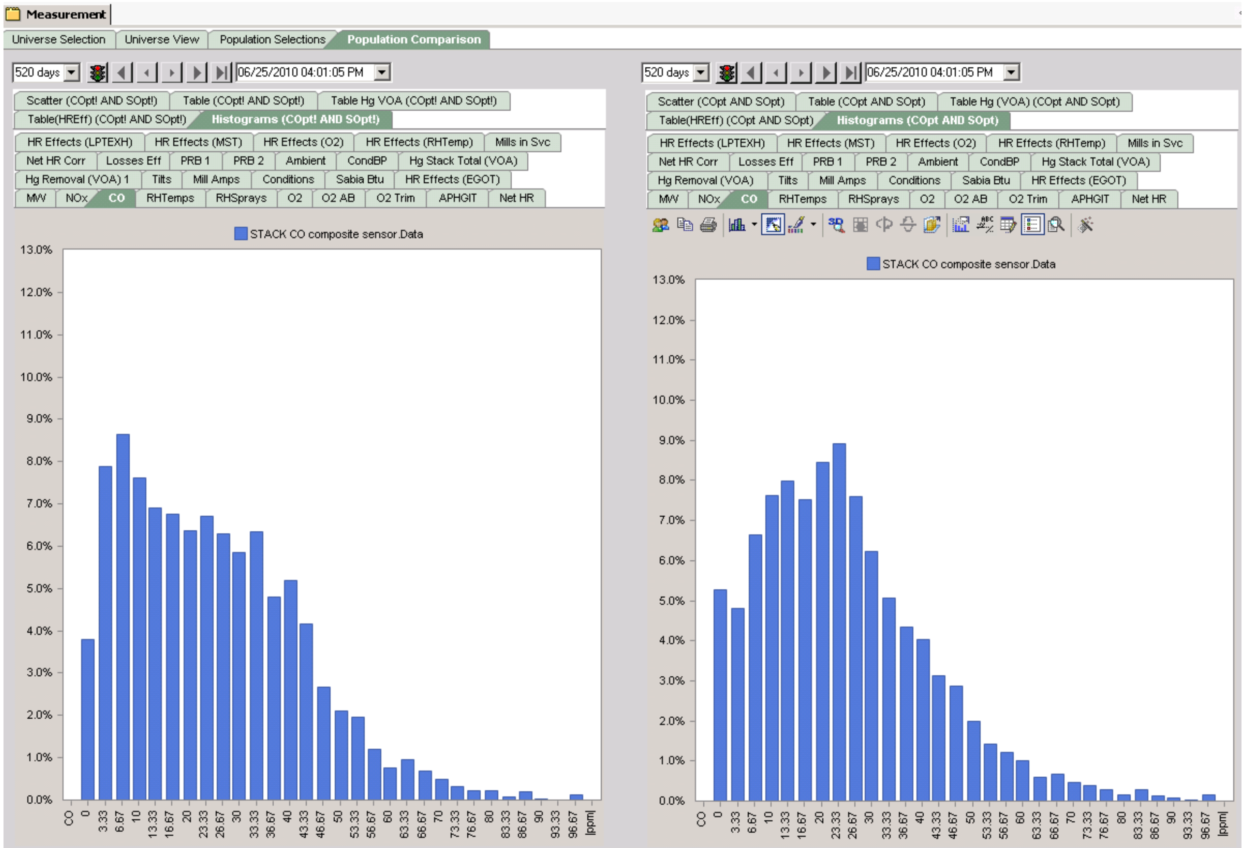

Figure 155: Stack CO OFF(Left) vs. ON(Right) populations

3.6.5.7 Boiler O2

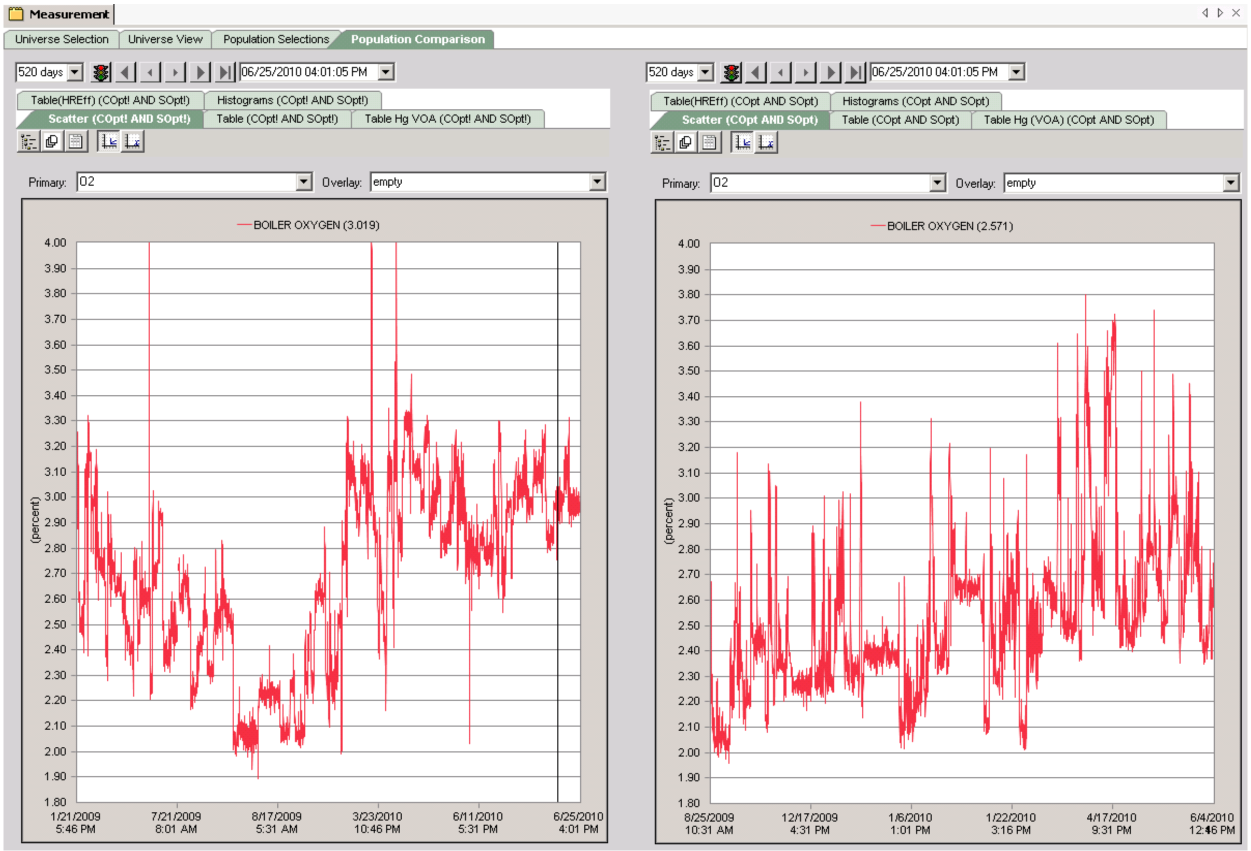

Figure 156: Boiler O2 OFF(Left) vs. ON(Right) populations

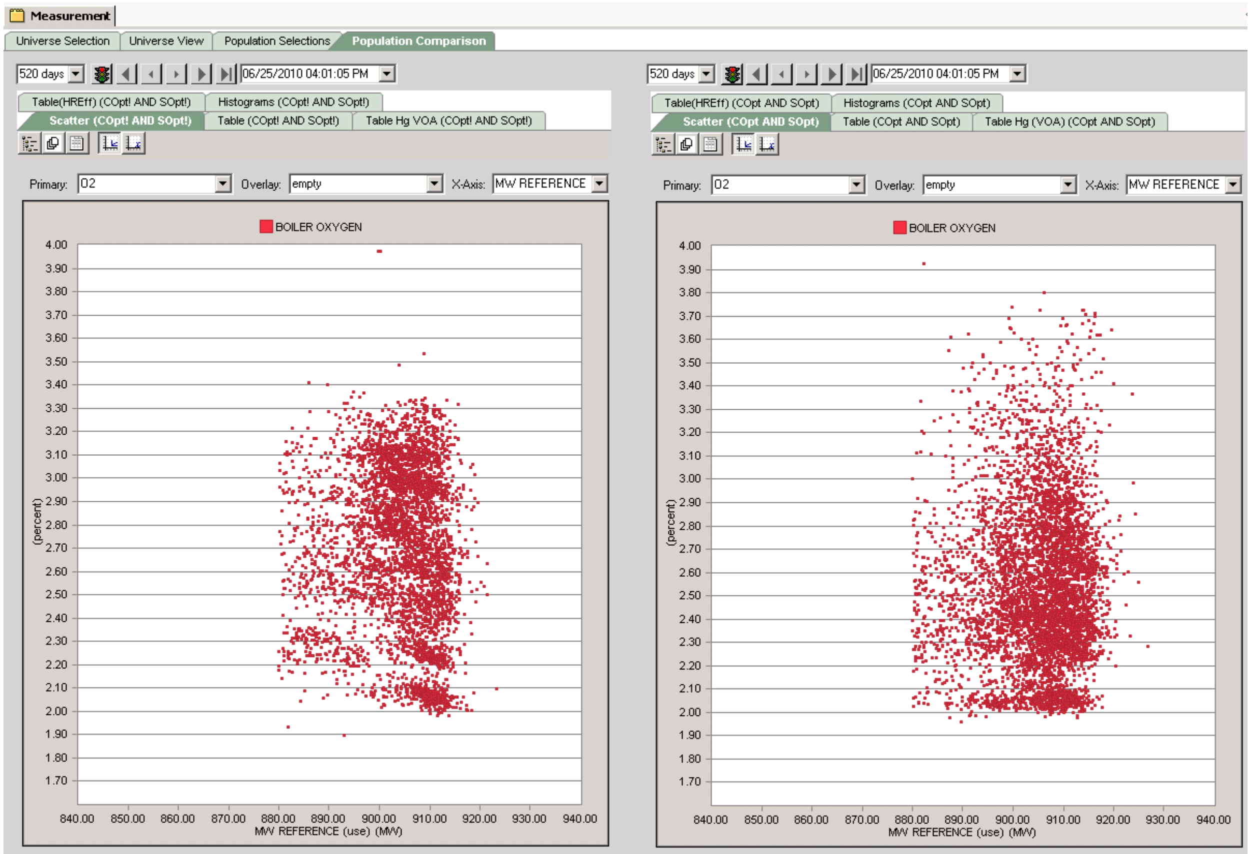

Figure 157: Boiler O2 OFF(Left) vs. ON(Right) populations

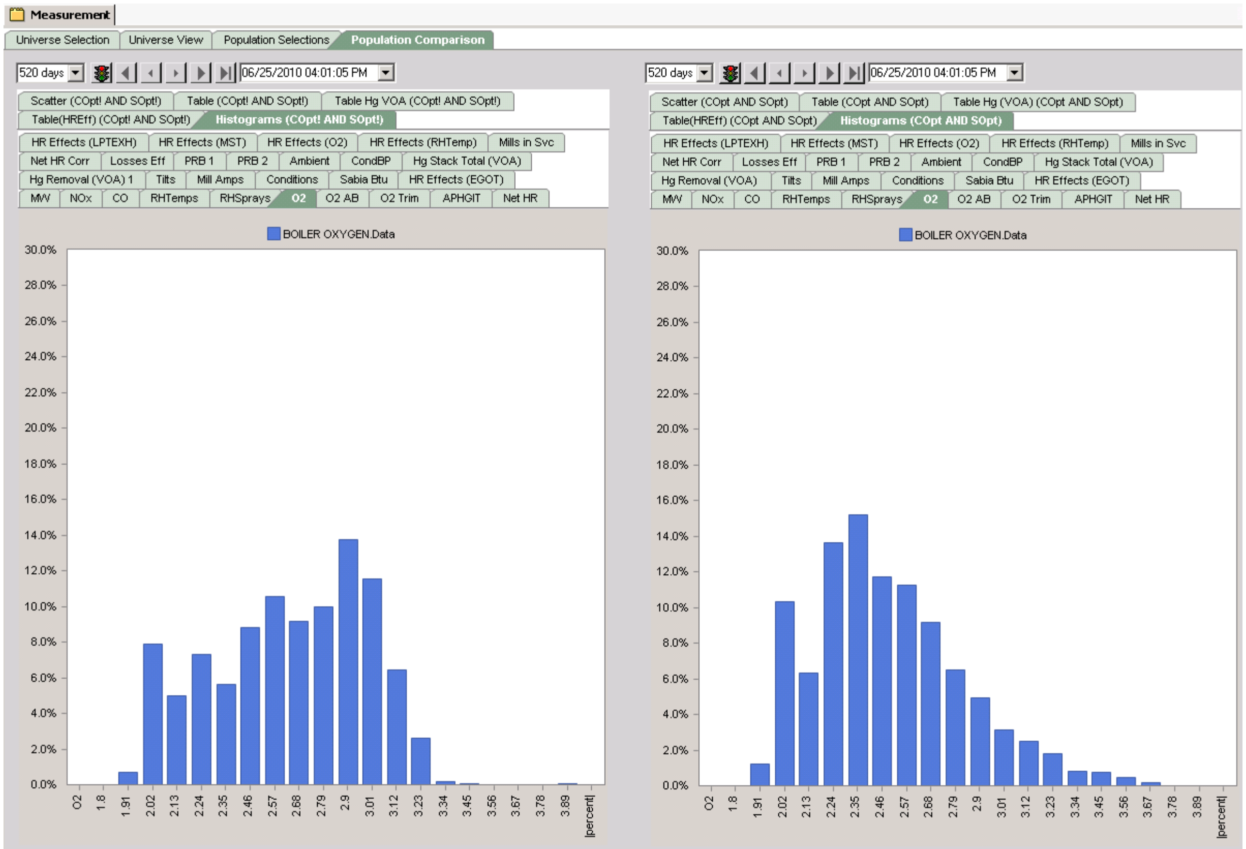

Figure 158: Boiler O2 OFF(Left) vs. ON(Right) populations

3.6.5.8 A and B Side O2

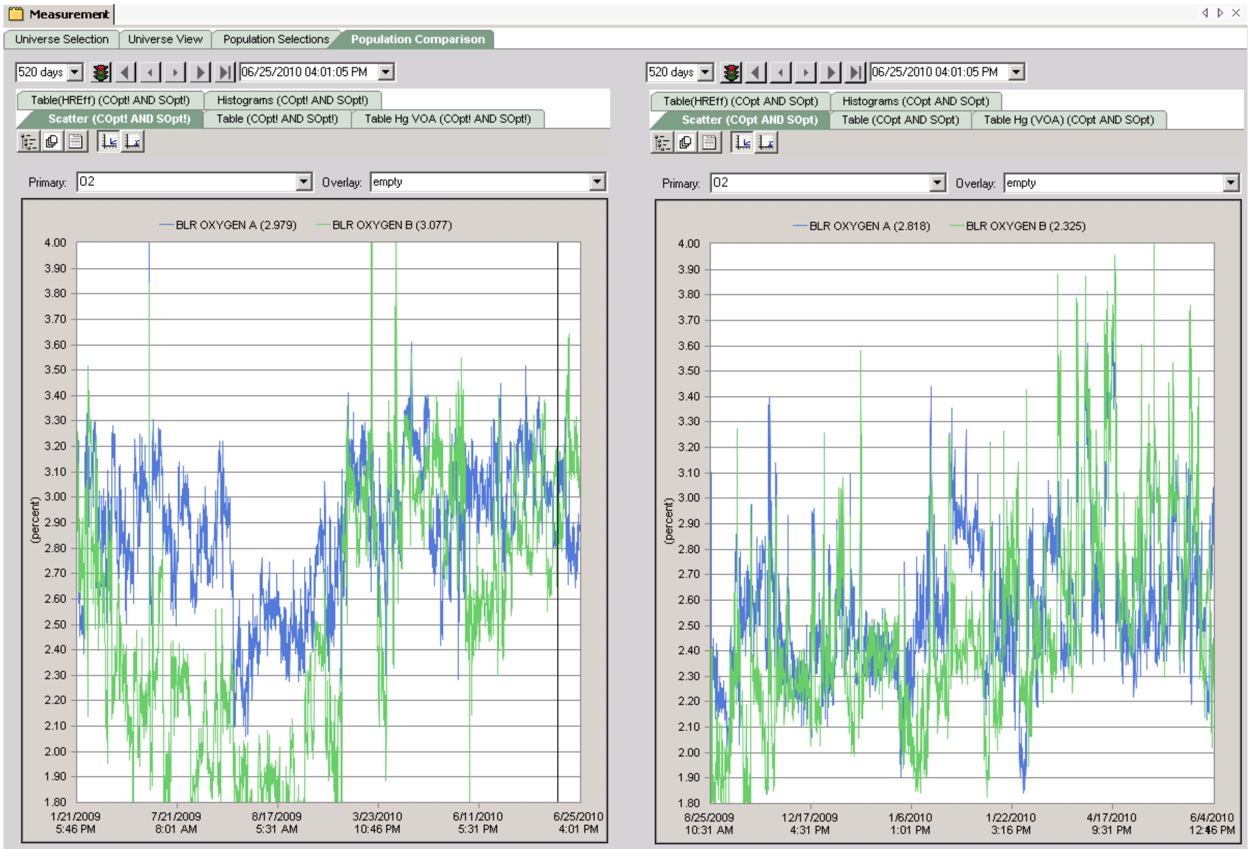

Figure 159: O2 A and B OFF(Left) vs. ON(Right) populations

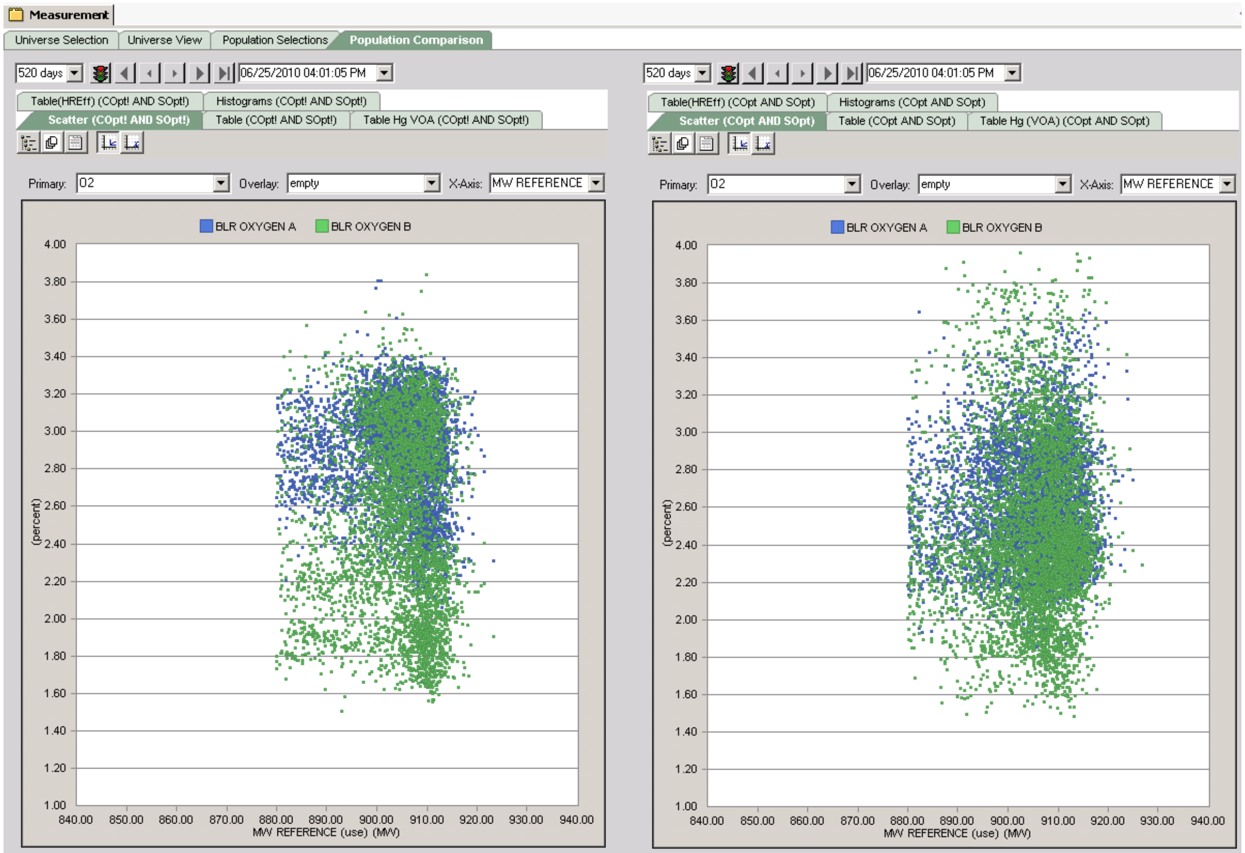

Figure 160: O2 A and B OFF(Left) vs. ON(Right) populations

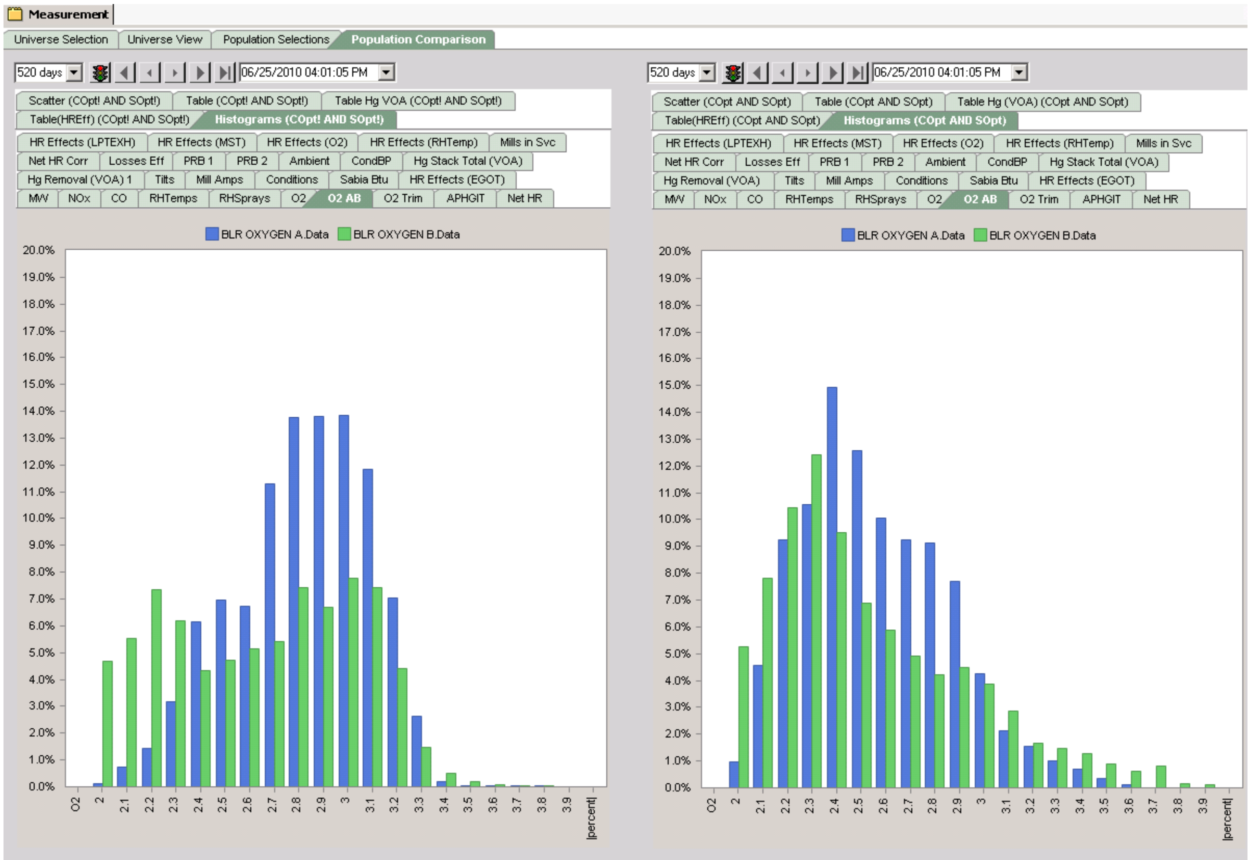

Figure 161: O2 A and B OFF(Left) vs ON(Right) populations

3.6.5.9 A and B Side RH Temps

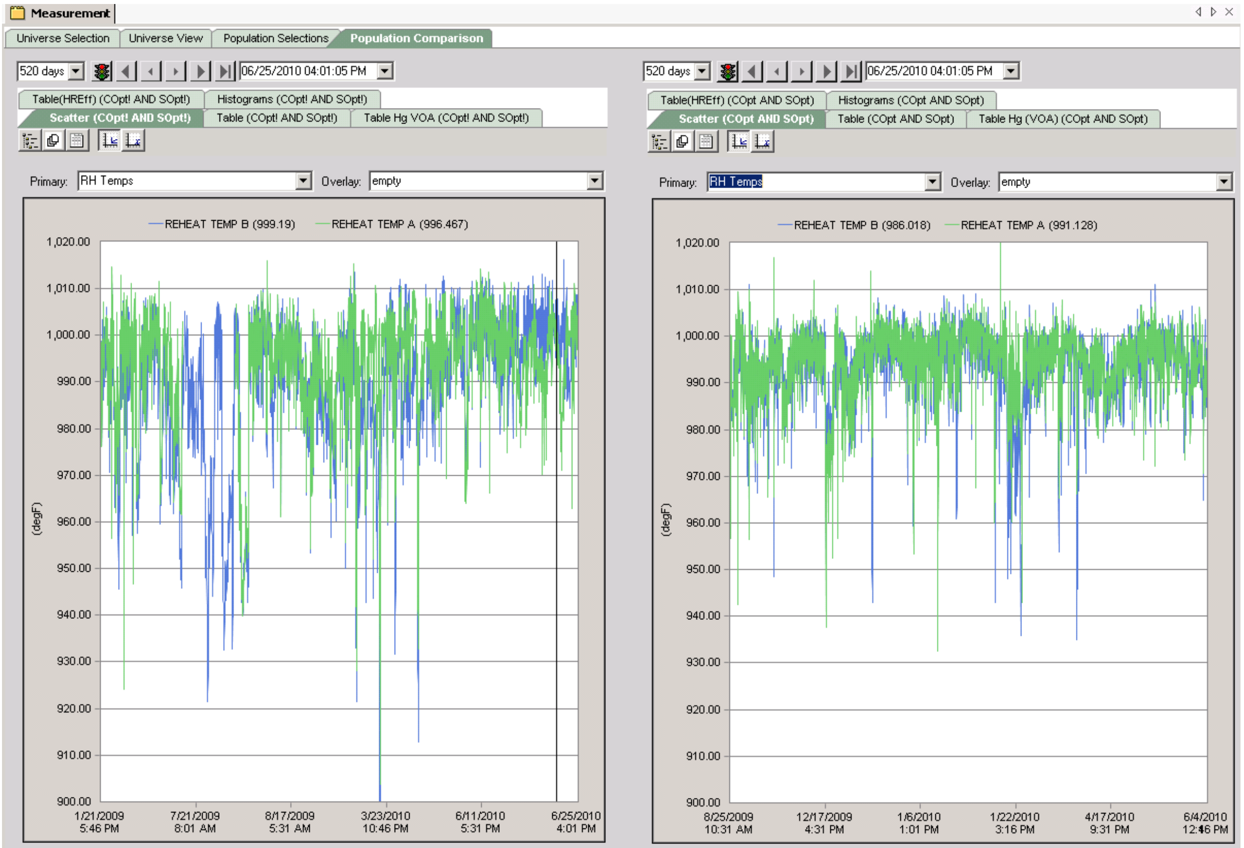

Figure 162: RH Temp A and B OFF(Left) vs ON(Right) populations

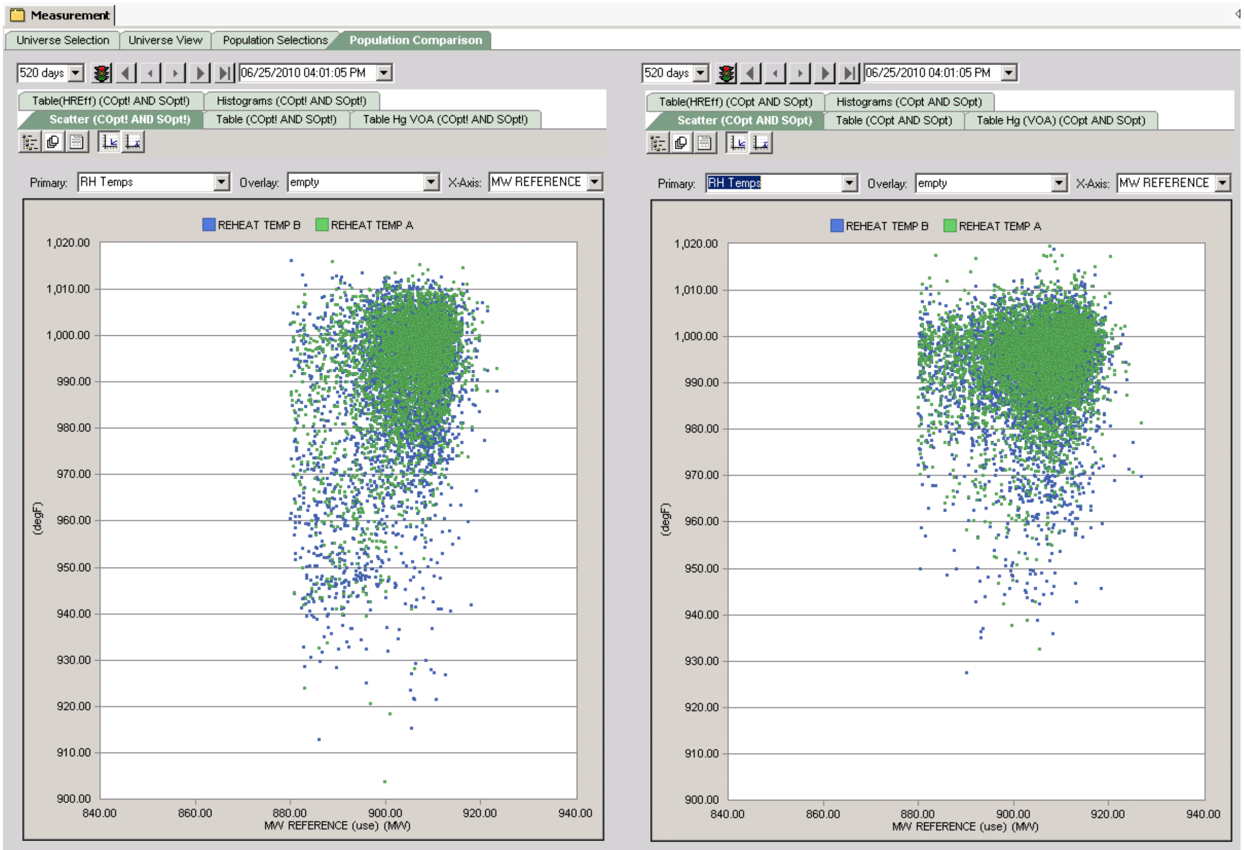

Figure 163: RH Temp A and B OFF(Left) vs ON(Right) populations

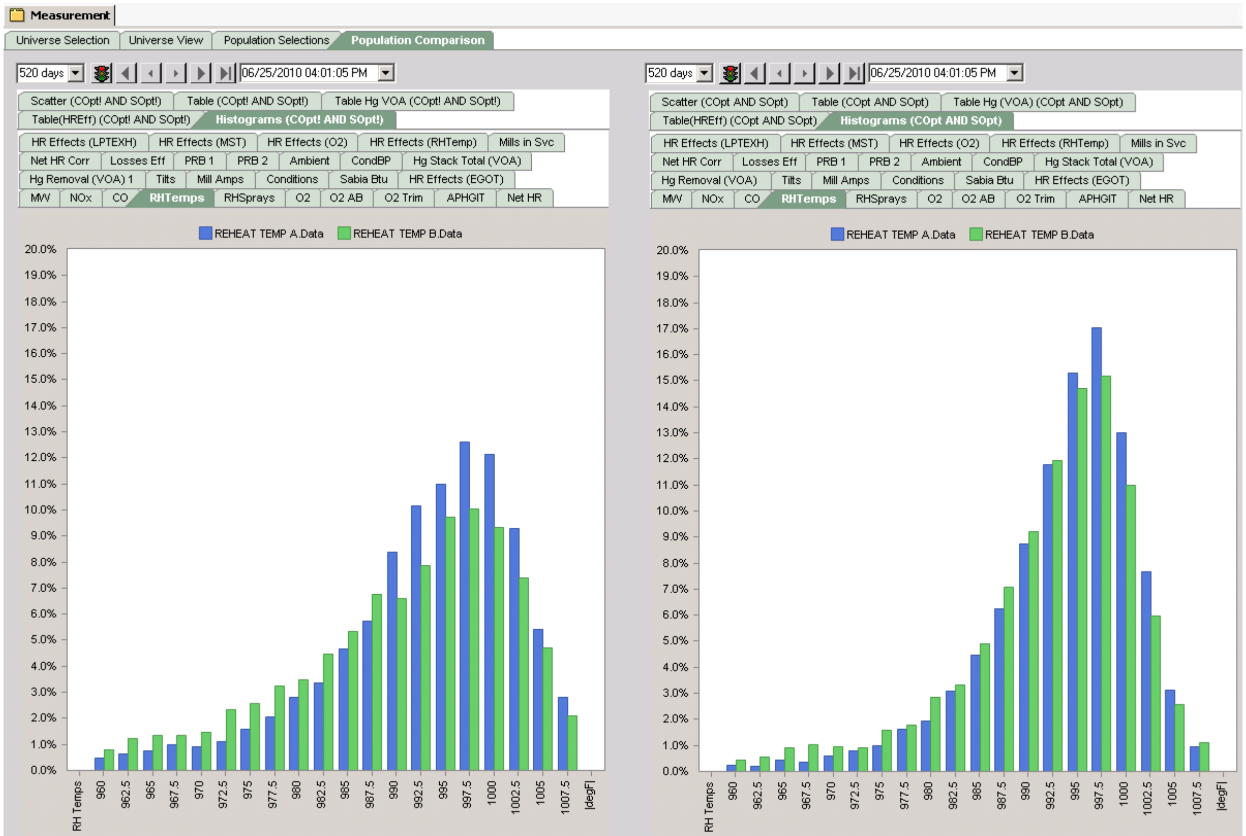

Figure 164: RH Temp A and B OFF(Left) vs ON(Right) populations

3.6.5.10 PCT PRB Disturbance

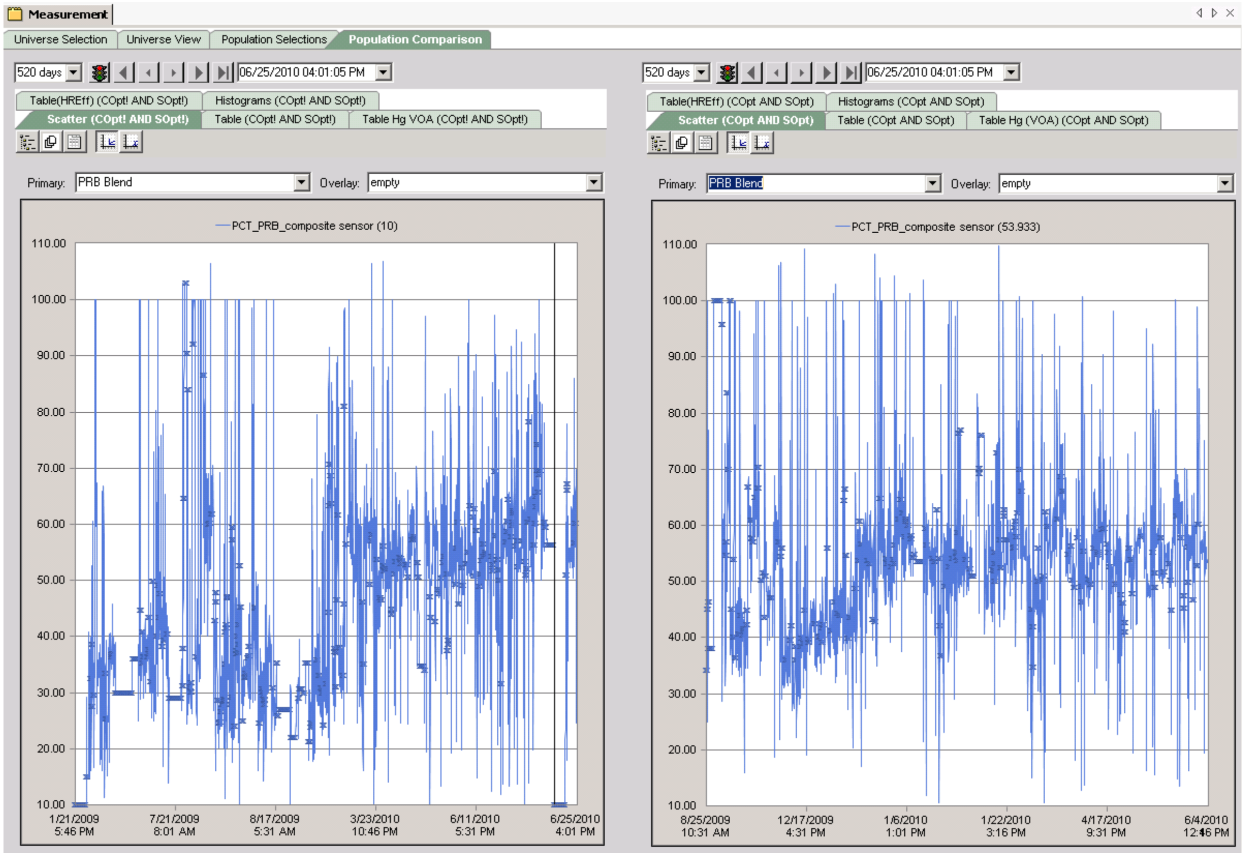

Figure 165: PCT PRB OFF(Left) vs ON(Right) populations

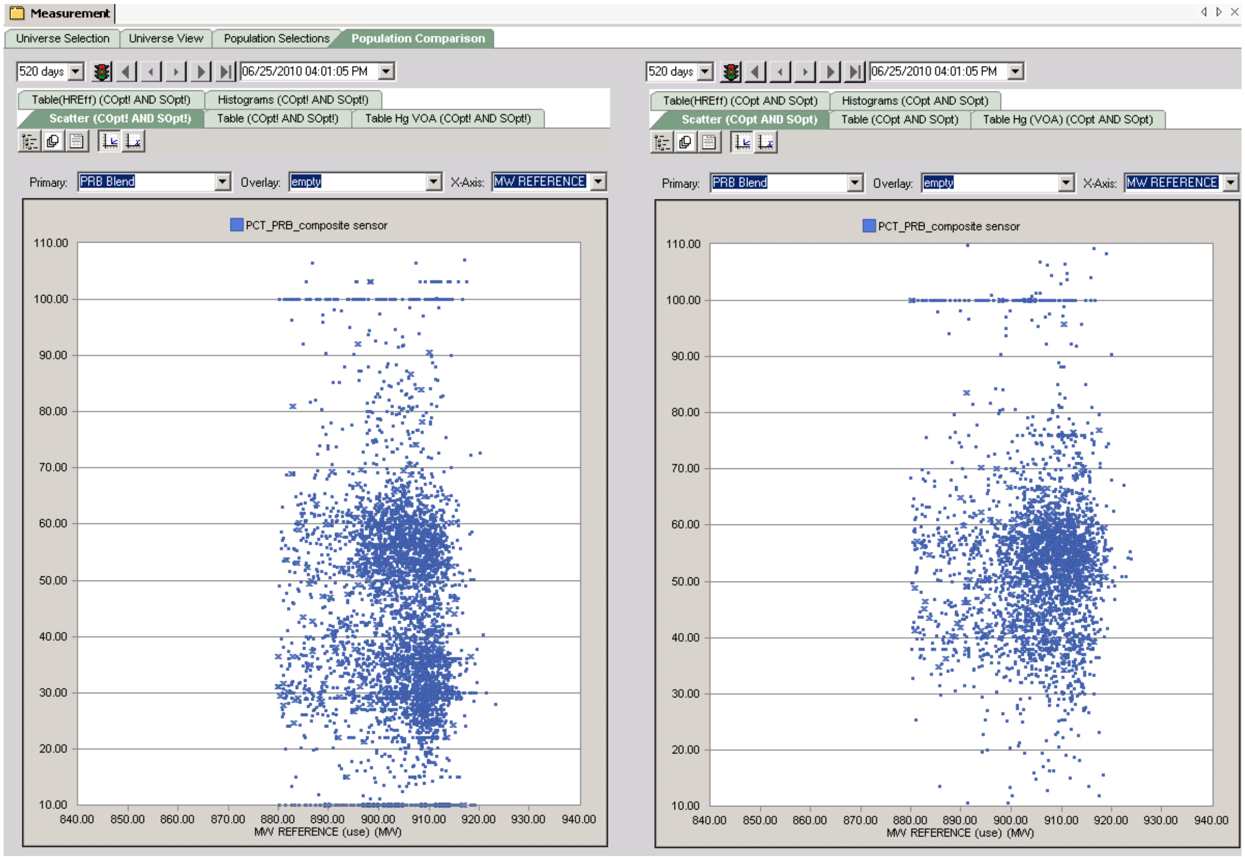

Figure 166: PCT PRB A and B OFF(Left) vs ON(Right) populations

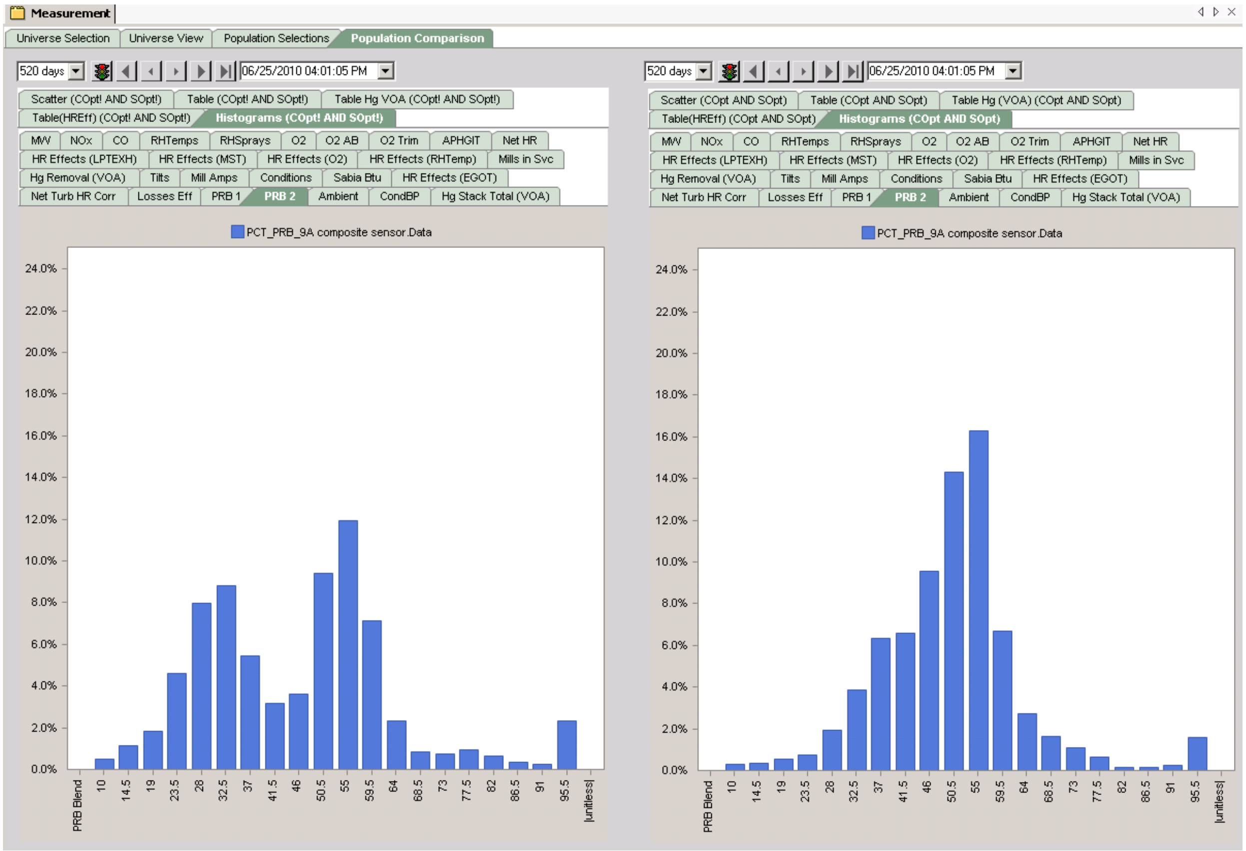

Figure 167: PCT PRB A and B OFF(Left) vs ON(Right) populations

3.6.5.11 Condenser Back Pressure Disturbance

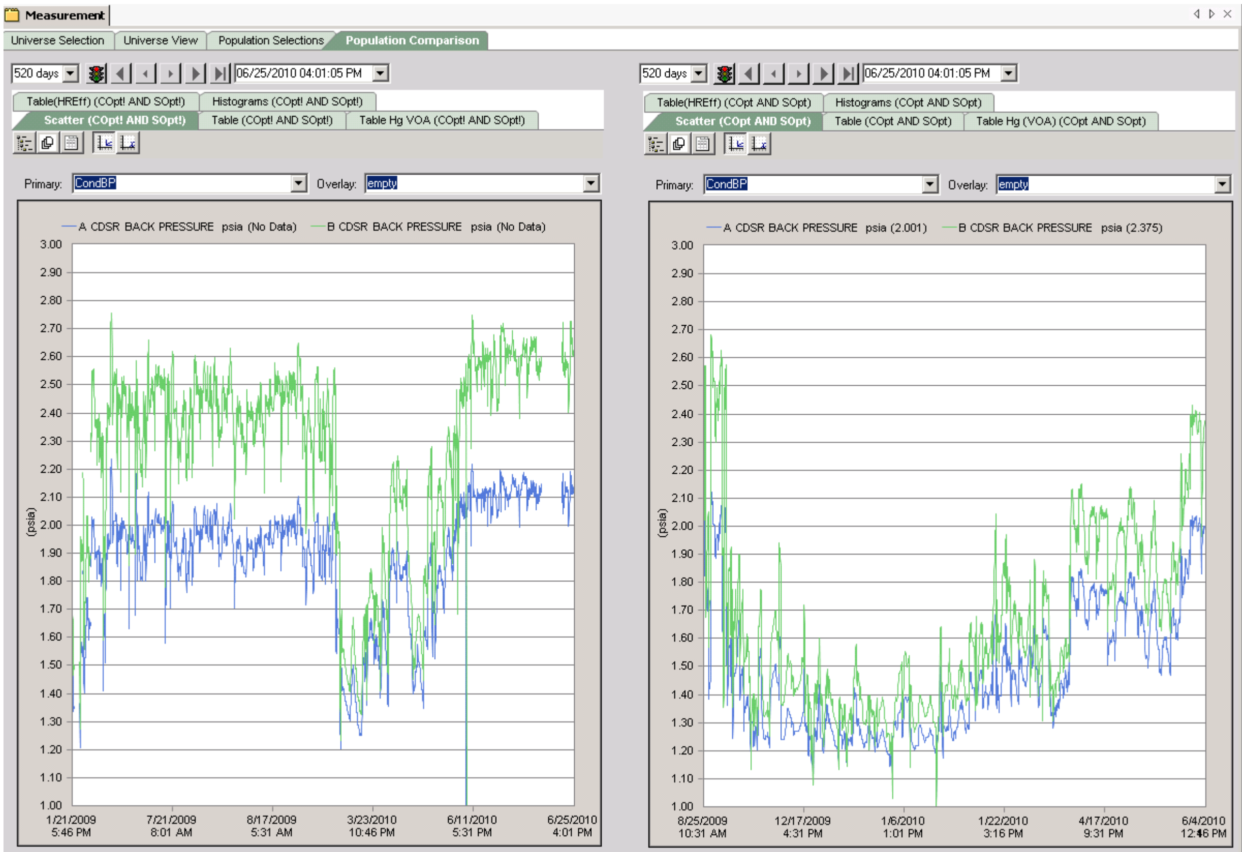

Figure 168: Cond Back Pressure A and B OFF(Left) vs ON(Right) populations

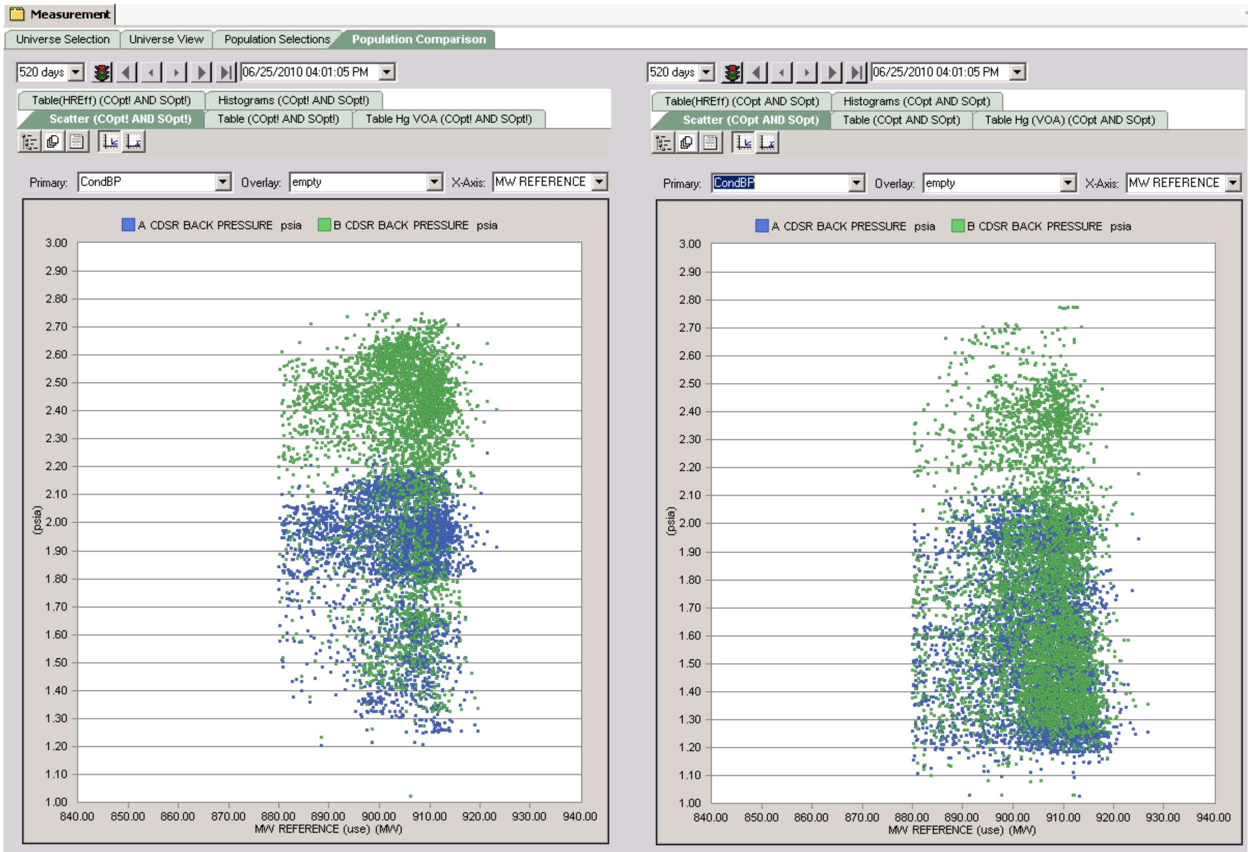

Figure 169: Cond Back Pressure A and B OFF(Left) vs ON(Right) populations

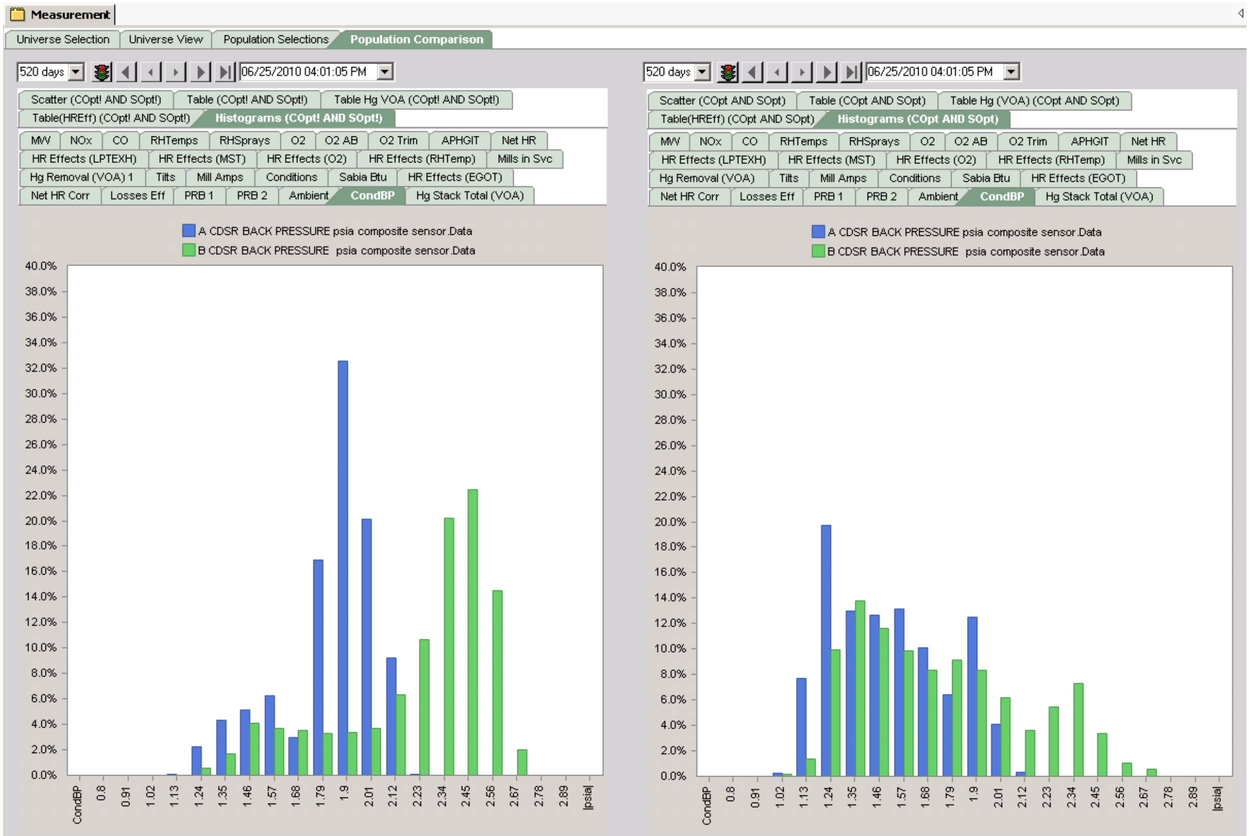

Figure 170: Cond Back Pressure A and B OFF(Left) vs ON(Right) populations

3.6.6 Recent Comparison of Populations

This section compares two populations selected from recent data (3/31/10 – 7/9/10). One population was selected to represent the control or "OFF" case, where no optimization was applied. The other was selected to represent data where optimization was applied.

The analysis of long term trends showed that the overall Hg Stack Total was significantly affected by fuel blend, per expectation. The Mercury Removal estimate (VOA) did not show this effect because it was blind to fuel. The analysis in this section assumes that a delta in mercury production of around 20% was seen over the long term (shown by the Mercury Models in section 3.6.2.3), and that a significant part of that was due to changing fuel blend. Because the fuel blend is normalized in the populations here (because more recent blending has been consistent at a ratio of around 50/50), this analysis asks what part of that change may have been due to optimization, or how much difference in Mercury production is seen when fuel blend is held constant and only optimization intensity is varied.

For this period, useful Heat Rate and Efficiency estimators were available. Their differences are shown here, however the difference in condenser back pressure and ambient conditions represent potentially significant disturbances in these dimensions. Lower condenser back pressure is favorable to Net Unit Heat Rate and so would bias the heat rate mean of that variable down in the ON population, meaning the improvement is likely less than it appears. Corrected Net Turbine Heat Rate however can be expected to be significantly isolated from condenser conditions because it is correct to "design conditions". The impact on Losses boiler efficiency of condenser back pressure would likely be negligible, and the impact of ambient conditions would be hard to predict for a given unit. Higher ambient temps affect different losses terms in ways that can be complex. Some data for Losses efficiency in the OFF population are suspect.

3.6.6.1 Data Selection

For the analysis shown, sampling was done at a frequency of 900 seconds for the period 3/31/10 – 7/9/10. From this universe, data points where load was not above 880MW were excluded. These samples were then classified according to the following criteria:

- OFF (control population): CombustionOpt Master Enable OFF AND SootOpt Master Enable OFF.
- ON (experimental population): CombustionOpt Master Enable ON AND SootOpt Master Enable ON and both O2Trim and Burner Tilt MV (manipulated variable) Enables ON.

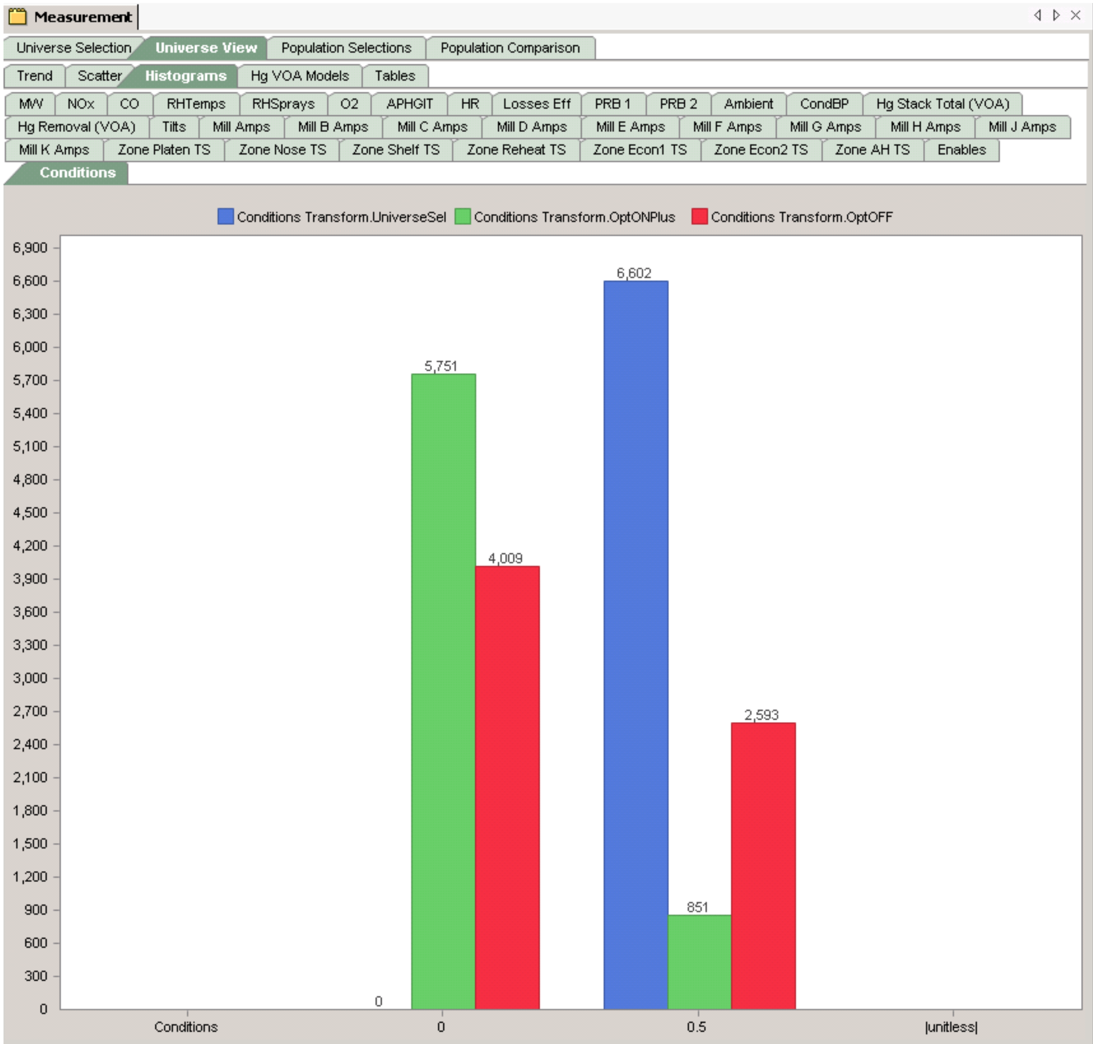

Figure 171: Experimental Data
Green represents ON, Red represents OFF, 1 equals True and 0 equals False. Blue represents the count of samples considered for selection into ON, OFF, or neither population.

3.6.6.2 Tabulation of Recent Population Means with Deltas

3/31/10 - 7/9/10, 15m, MW>880, ONPlus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
Hg Stack Total (VOA)	µg/m3	5.48	5.21	-0.27	-4.9%	Down
Hg Removal	%	62.18	63.63	1.45	2.3%	Up

Table 13: Tabulated Comparison of KPI (Hg)

3/31/10 - 7/9/10, 15m, MW>880, ONPlus O2 and Tilts						
KPI	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**	**Objective**
NOx	lb/MMBtu	0.218	0.182	-0.036	-16.5%	Down
CO	ppm	33.08	25.15	-7.93	-24.0%	< 40
RH Temp A	degF	995.78	994.51	-1.27	-0.1%	>980
RH Temp B	degF	995.51	993.91	-1.6	-0.2%	>980
O2 A	%	3.05	2.68	-0.37	-12.1%	>2
O2 B	%	2.94	2.86	-0.08	-2.7%	>2
Boiler O2	%	3	2.77	-0.23	-7.7%	>2
Tilt Dmd A	%	70.87	56.27	-14.6	-20.6%	Down
Tilt Dmd B	%	66.73	59.26	-7.47	-11.2%	Down
2A APH Gas Inlet	degF	779.58	774.37	-5.21	-0.7%	<780
2B APH Gas Inlet	degF	771.25	767.29	-3.96	-0.5%	<780
Losses Effic	%	81.84	81.84	0	0.00%	Up
Net Unit HR	Btu/kWh	10323.46	10202.99	-120.47	-1.17%	Down
Net Turbine HR (Corr)	Btu/kWh	8261.55	8218.69	-42.86	-0.52%	Down

Table 14: Tabulated Comparison of KPI (non-Hg)

Table 14 shows the means for the ON and OFF populations.

3/31/10 - 7/9/10, 15m, MW>880, ONPlus O2 and Tilts					
Disturbance	**Units**	**OFF**	**ON**	**Delta**	**Pct Change**
Load	MW	902.55	905.43	2.88	0.3%
Fuel Heating Value	Btu/lb	6389.93	6387.07	-2.86	-0.04%
PCT PRB	%	52.65	55.64	2.99	5.68%
Cond BP	inH2O	2.19	1.86	-0.33	-15.07%
Ambient	degF (wetbulb)	84.88	76.34	-8.54	-10%

Table 15: Tabulated Comparison of Disturbances

The list of KPI's in Table 13 - Table 15 is not generally comprehensive, but it is fairly comprehensive for LMS U2. Each unit pushes against the common physical constraints of combustion and heat transfer processes in different ways, due to different specific characteristics of each boiler. For instance LMS U2 does not use SH or RH sprays, key KPI's that for most units would definitely be shown here. The list of variables represents benefits in an appropriately multi-variable way for LMS U2, given the processes being addressed and the instrumentation available.

Table 12 shows the means for the major disturbances that can affect the experiment. Load is not an issue, nor is Fuel Heating Value. The difference in fuel blend ("PCT PRB") is also probably negligible. Differences in condenser back pressure and ambient conditions however represent possibly significant causal disturbances compromising the isolation of the experimental factor (which is Optimization ON or OFF) in the heat rate and efficiency dimensions.

3.6.6.3 Population Comparison Plots

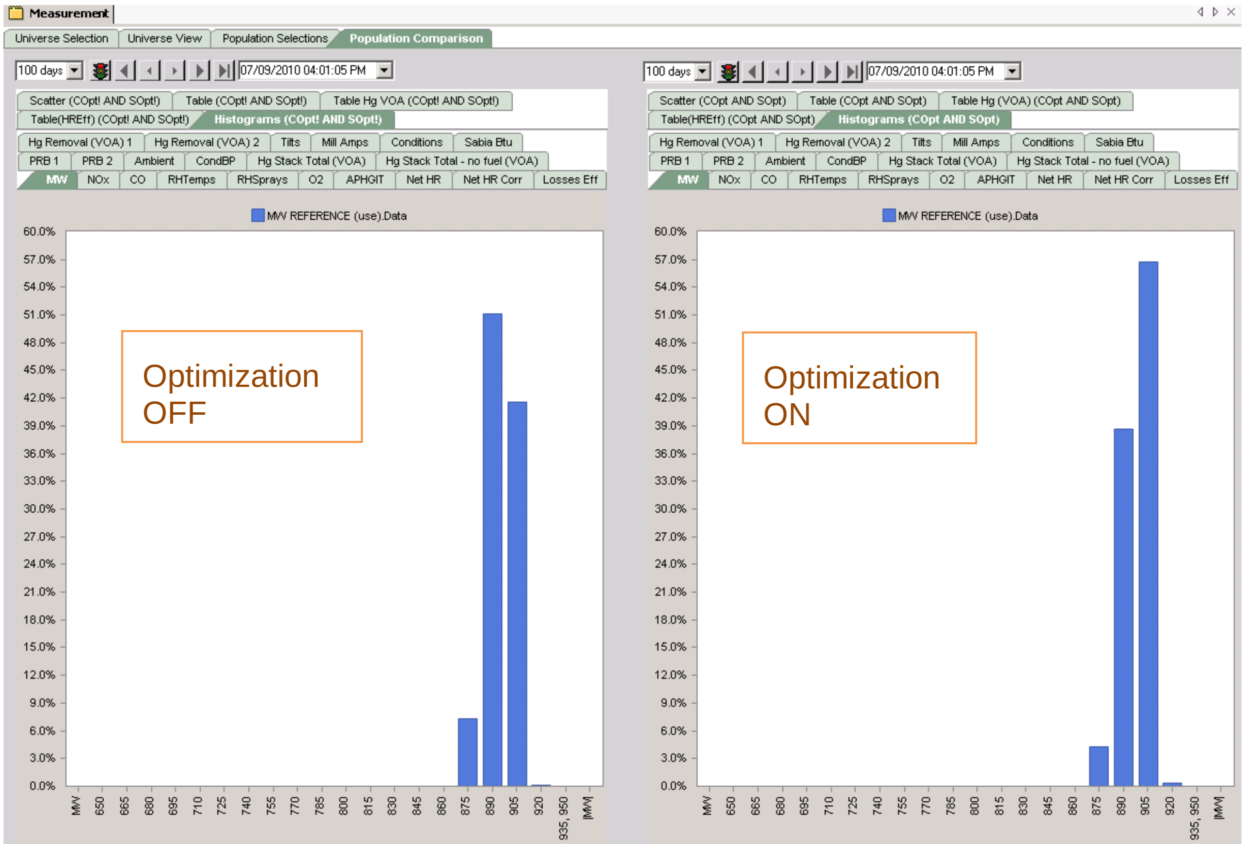

Figure 172: Comparison Plots

The plots and tables shown in the following sections (pages 208 to 223) compare populations of data where optimization was active to populations where it was not. OFF, or control data, is always on the left. ON, or experiment data, is always on the right, as shown in Figure 172. Plots include data series plots (non-continuous time series), histograms, which show the relative distribution of values for the variable in question, and scatter plots vs. Load.

3.6.6.4 Mercury

The data for Hg Removal is from the Hg removal Model (or Virtual On-Line Analyzer) described in section 3.5.

3.6.6.4.1 Mercury Removal (VOA)

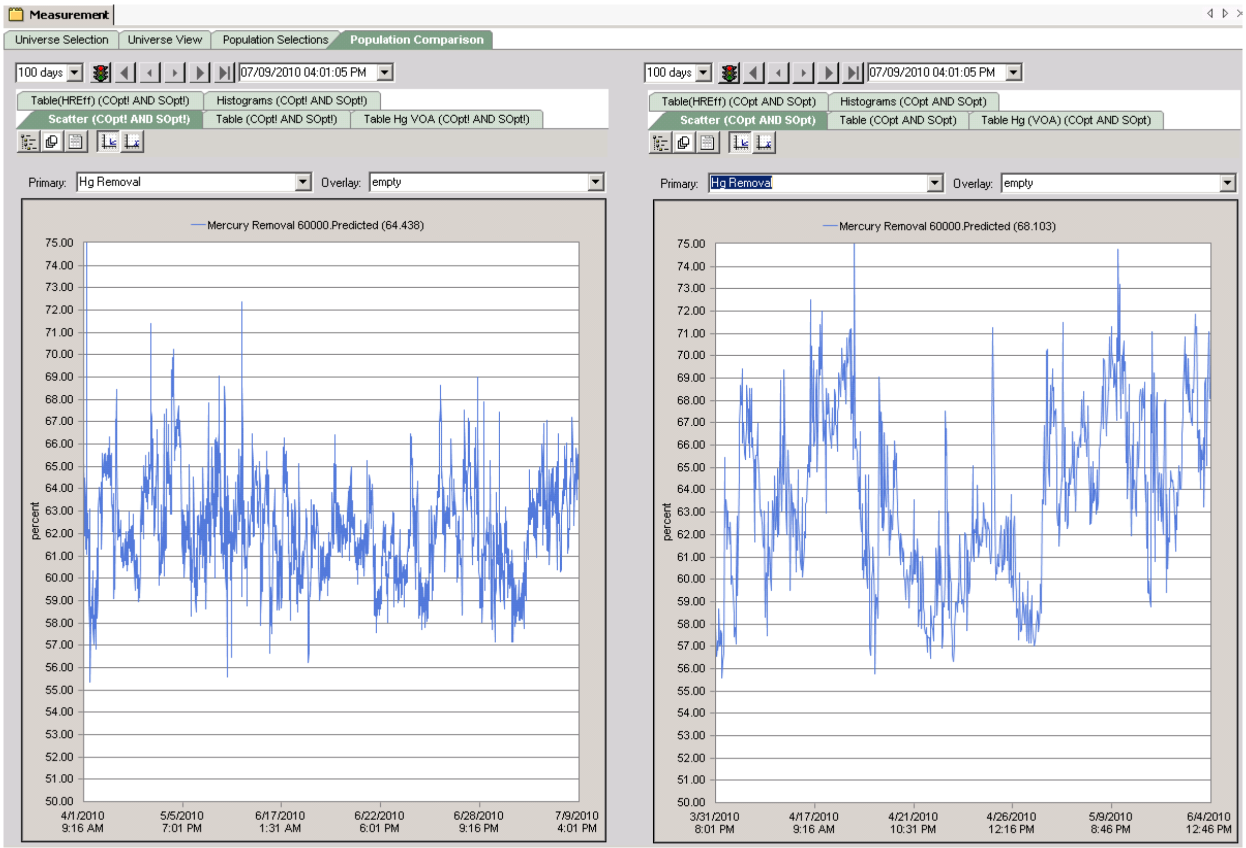

Figure 173: Hg Removal, VOA predicted f(O2,Tilts,MW), MW >880, 3/31/10 - 7/9/10

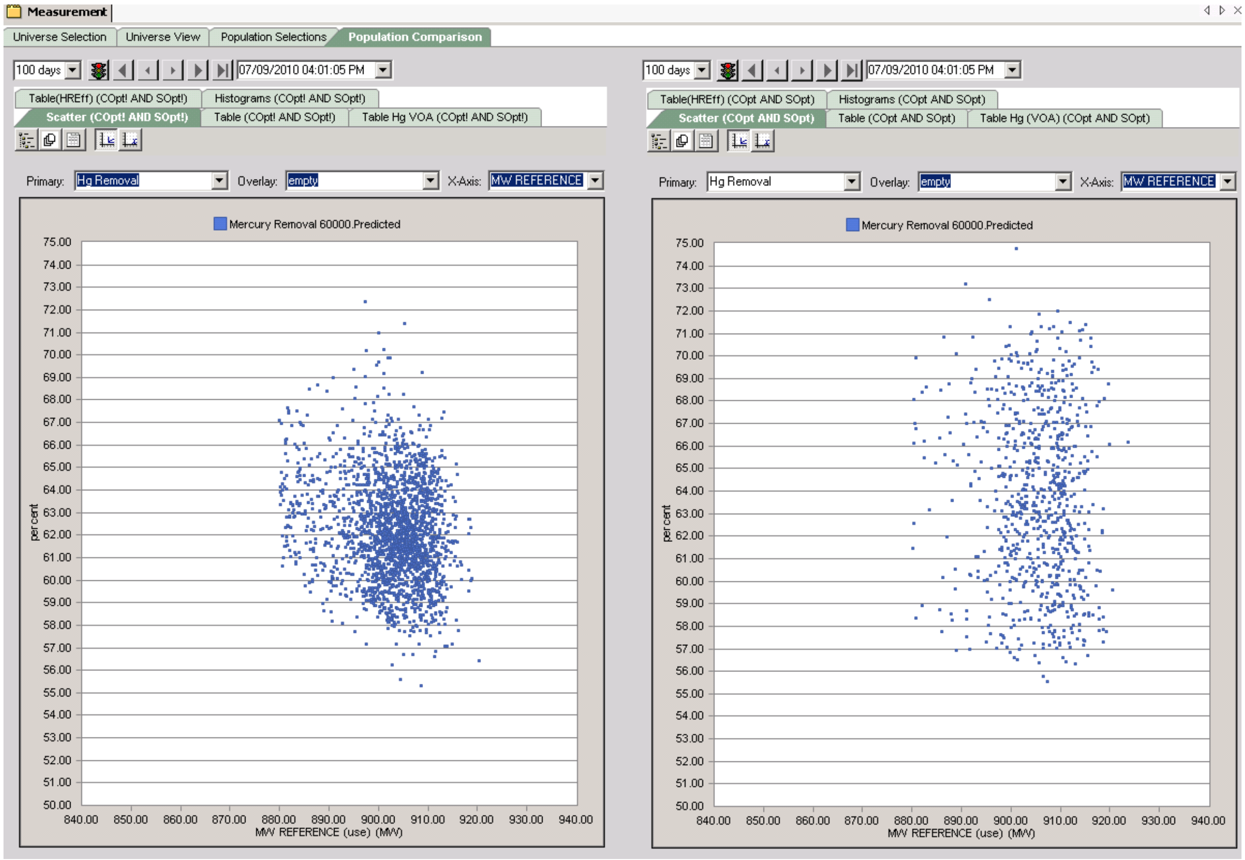

Figure 174: Hg Removal, VOA predicted f(O2,Tilts,MW), MW >880, 3/31/10 - 7/9/10

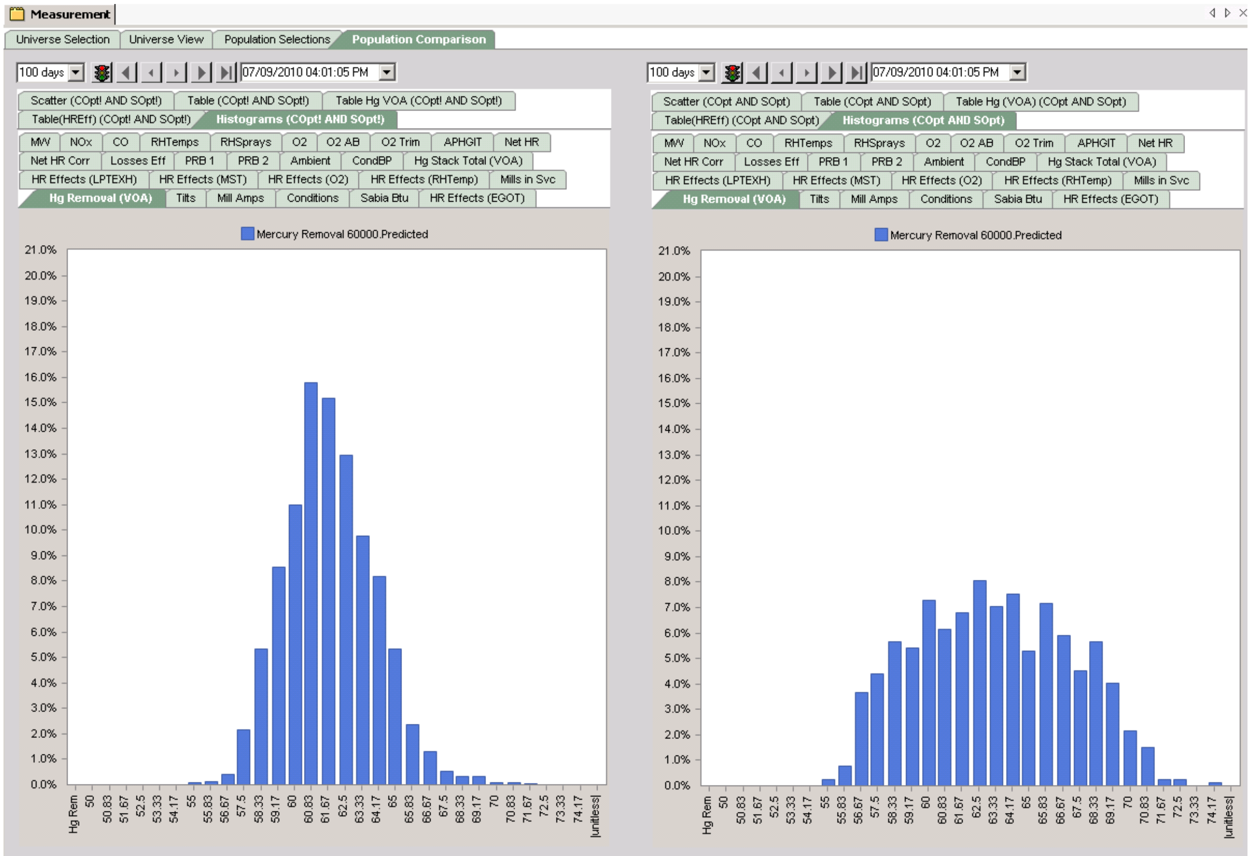

Figure 175: Hg Removal, VOA predicted f(O2,Tilts), MW >880, 3/31/10 - 7/9/10

3.6.6.4.2 *Mercury Stack Total (VOA)*

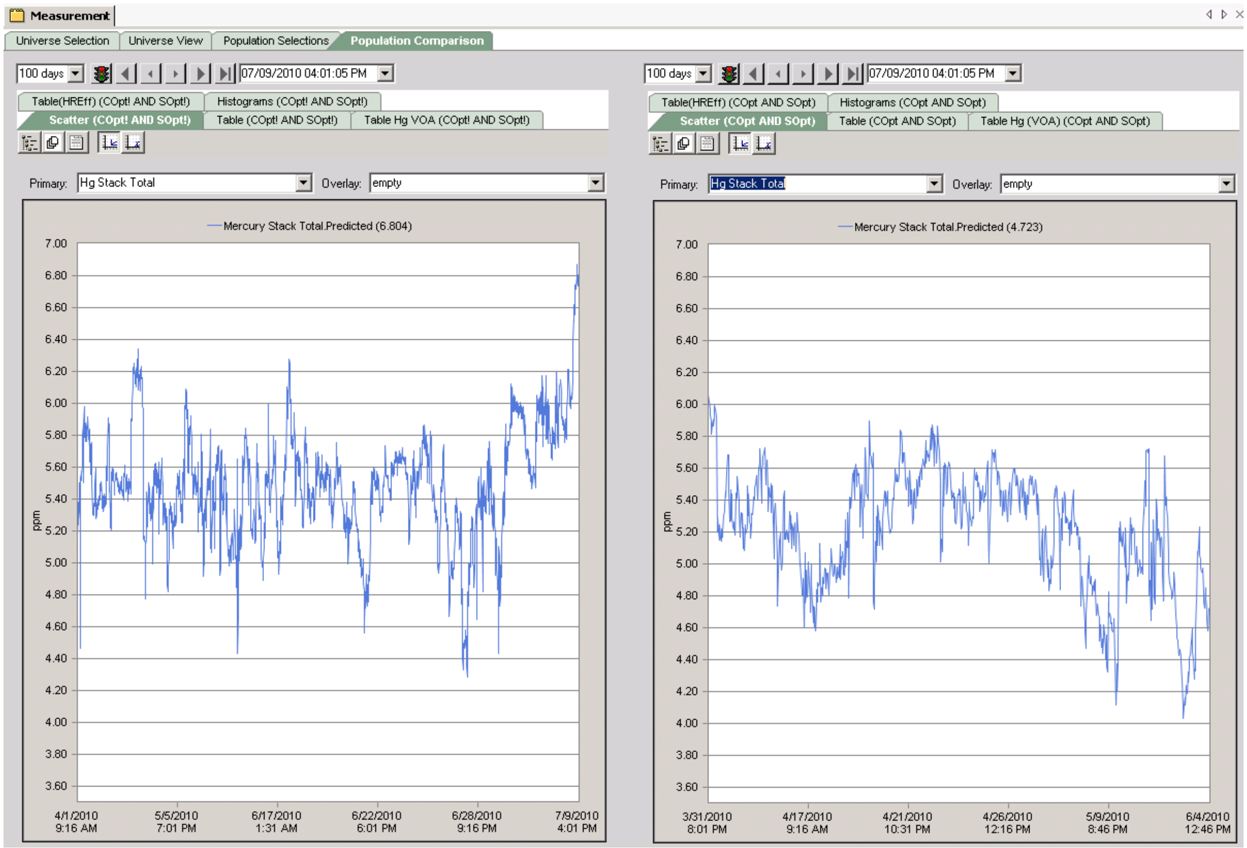

Figure 176: Hg Stack Total, VOA predicted f(O2,Tilts,MW,Blend), MW >880, 3/31/10 - 7/9/10

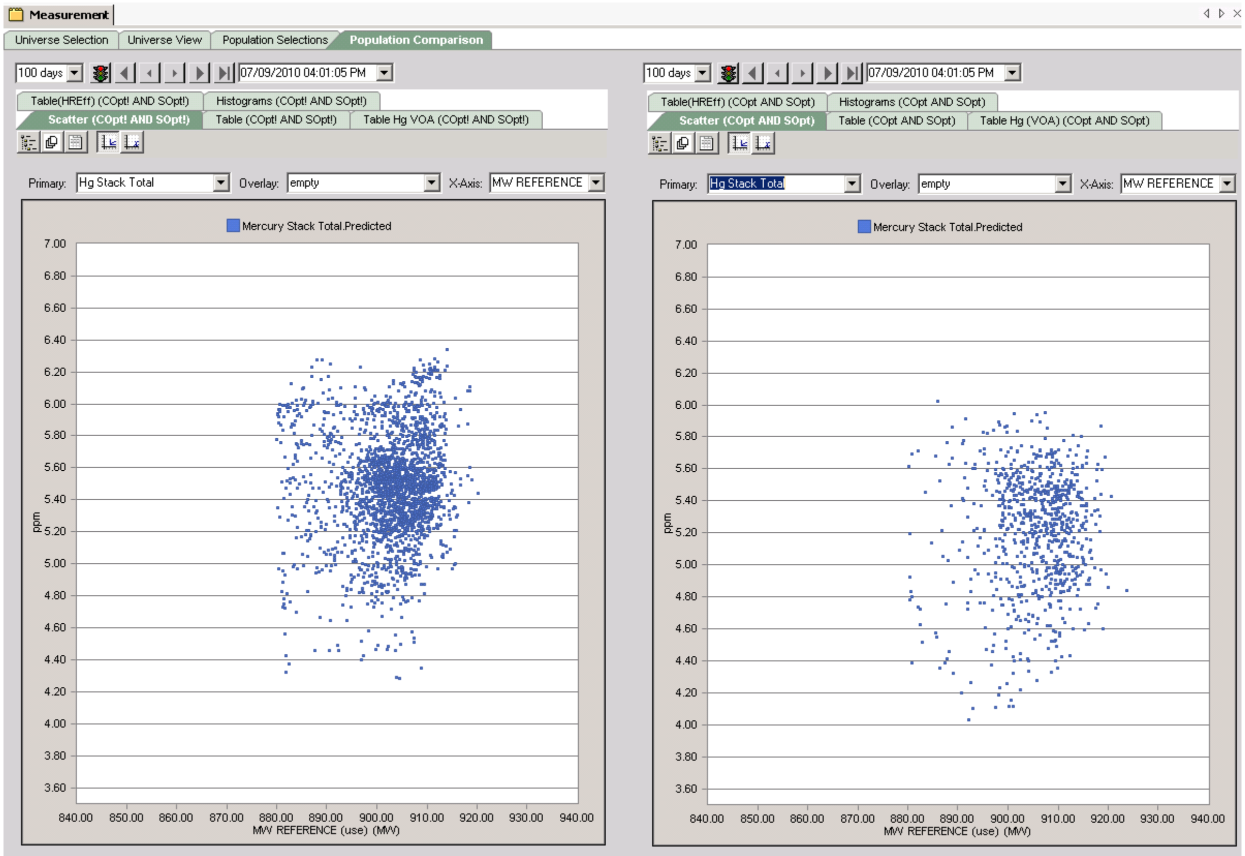

Figure 177: Hg Stack Total, VOA predicted f(O2,Tilts,MW,Blend), MW >880, 3/31/10 - 7/9/10

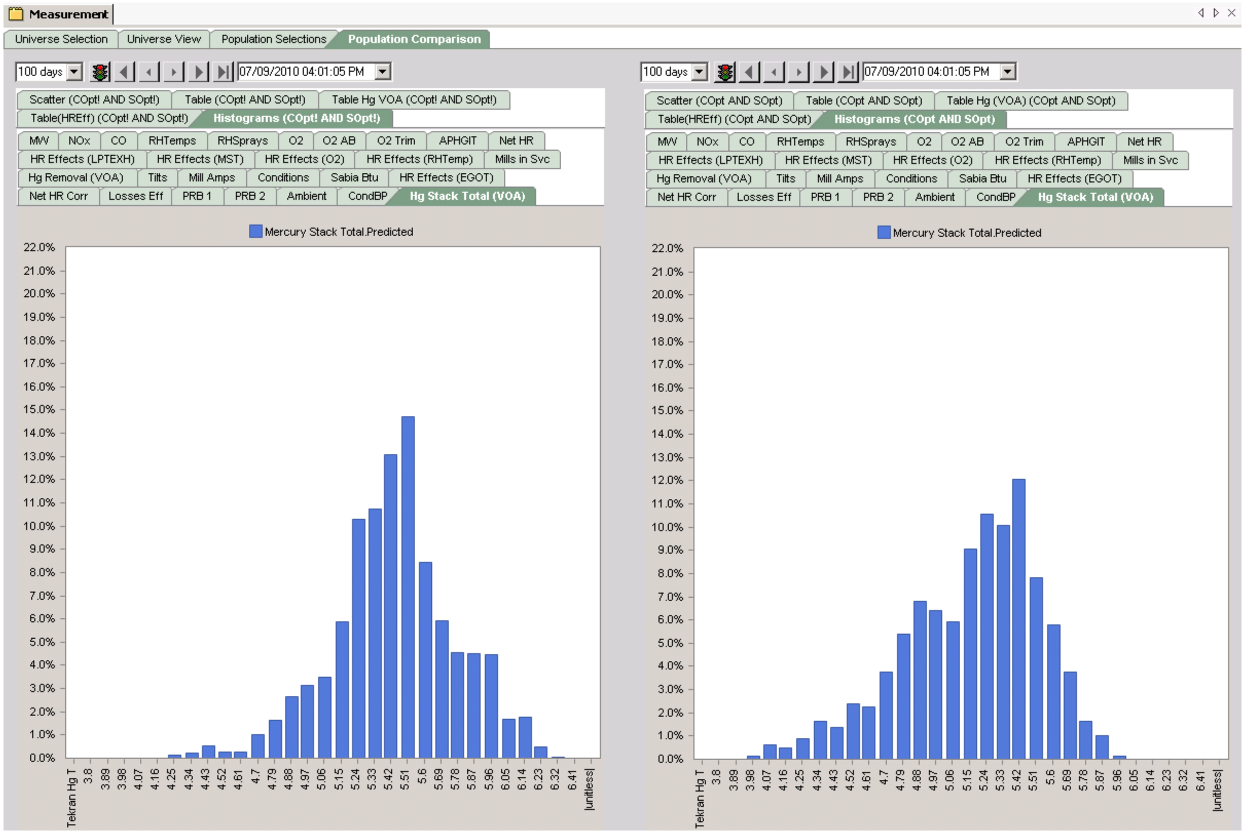

Figure 178: Hg Stack Total, VOA predicted f(O2,Tilts,MW,Blend), MW >880, 3/31/10 - 7/9/10

3.6.6.5 NOx

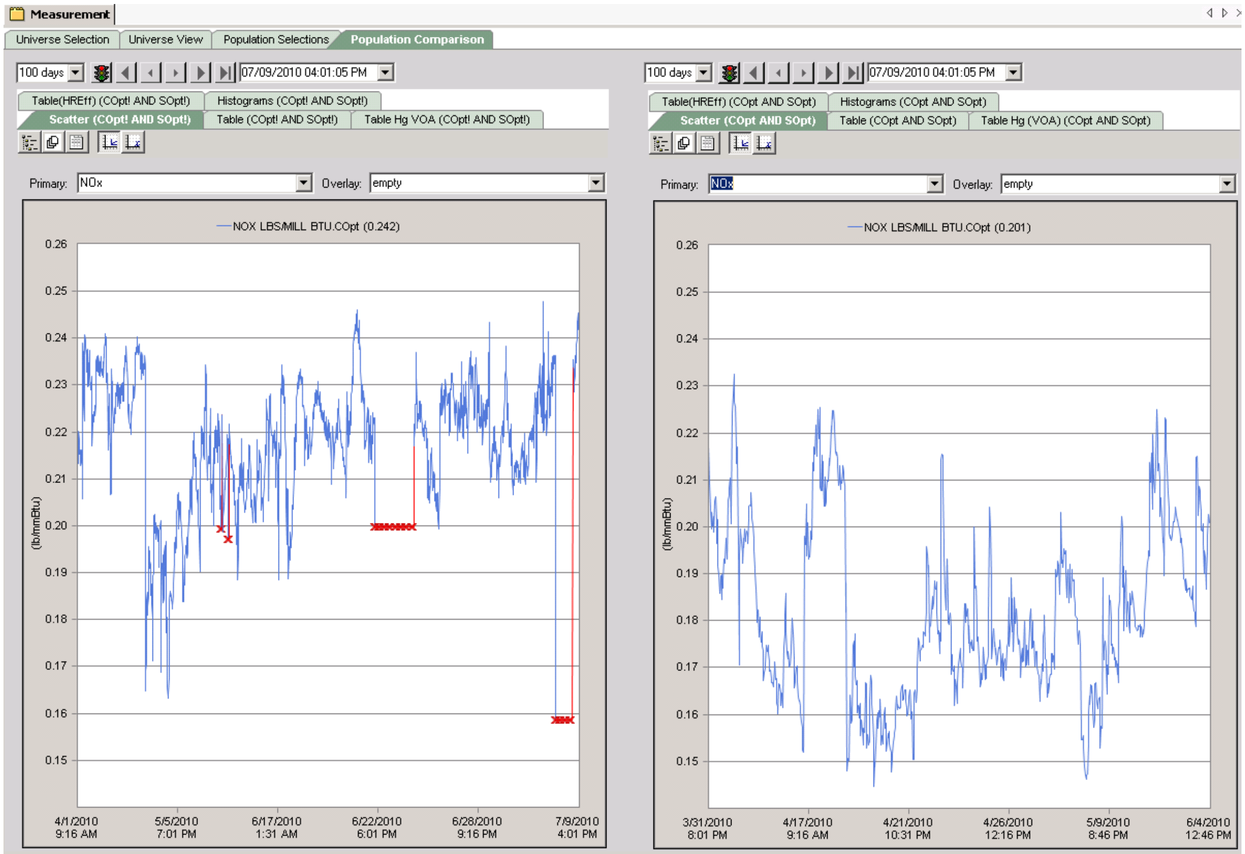

Figure 179: CEMS NOx, MW>880, 3/31/10 - 7/9/10

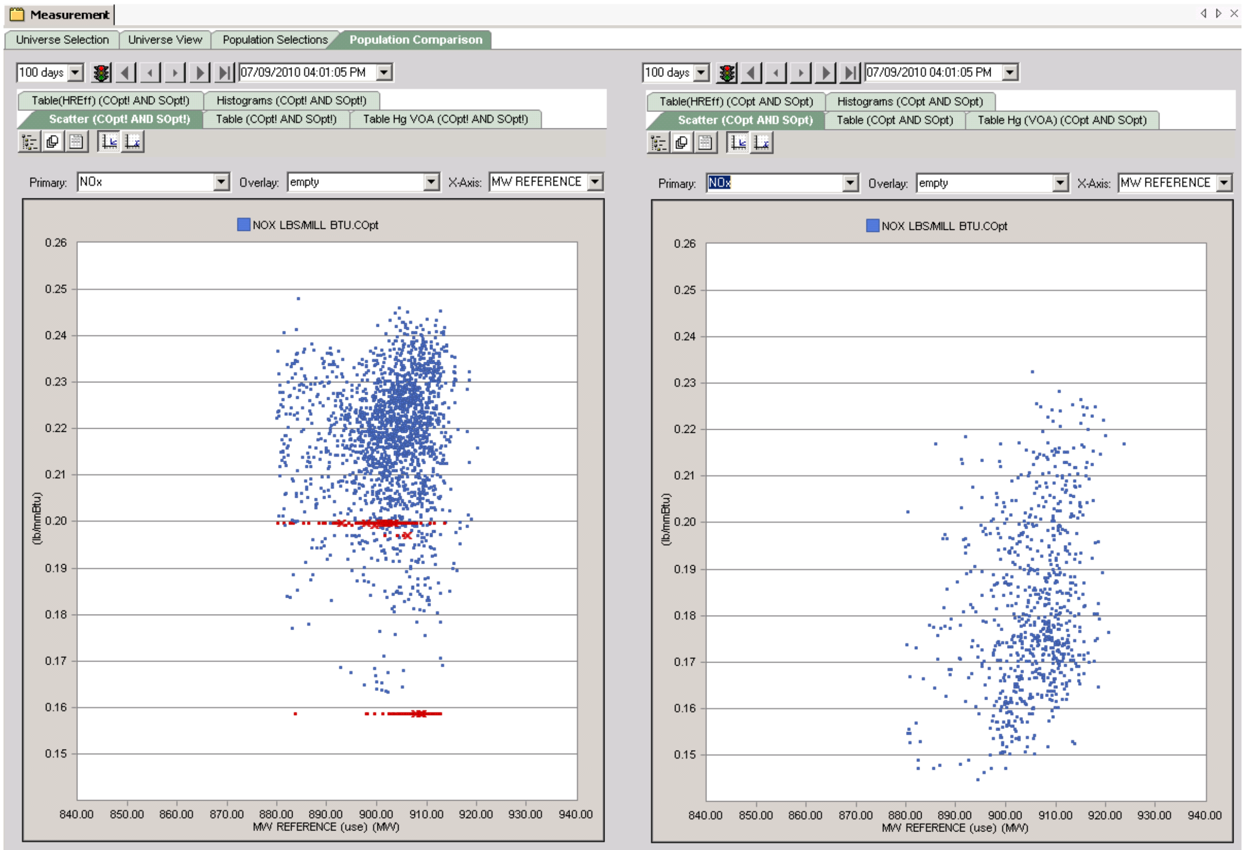

Figure 180: CEMS NOx, MW>880, 3/31/10 - 7/9/10

Red indicates data with bad status, not included in calculation of mean

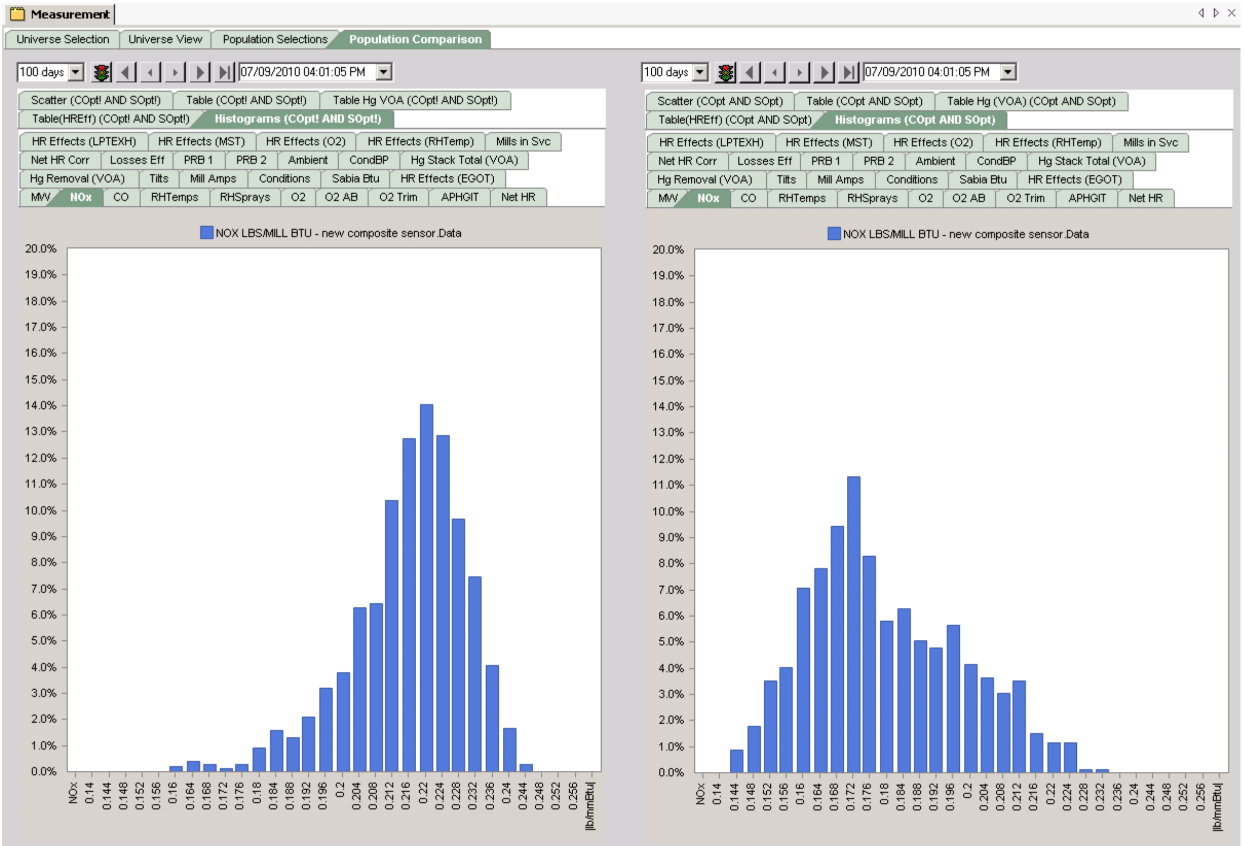

Figure 181: CEMS NOx, MW>880, 3/31/10 - 7/9/10

3.6.6.6 CO

CO was a “maximum limit” objective in the optimization profile, set to 30 ppm. The difference seen in CO shows that the optimizer was successfully limiting CO statistically to a threshold of around 35-40 ppm. CO is a noisy process, typical practice is to set the optimizer limit to a value lower than the desired threshold.

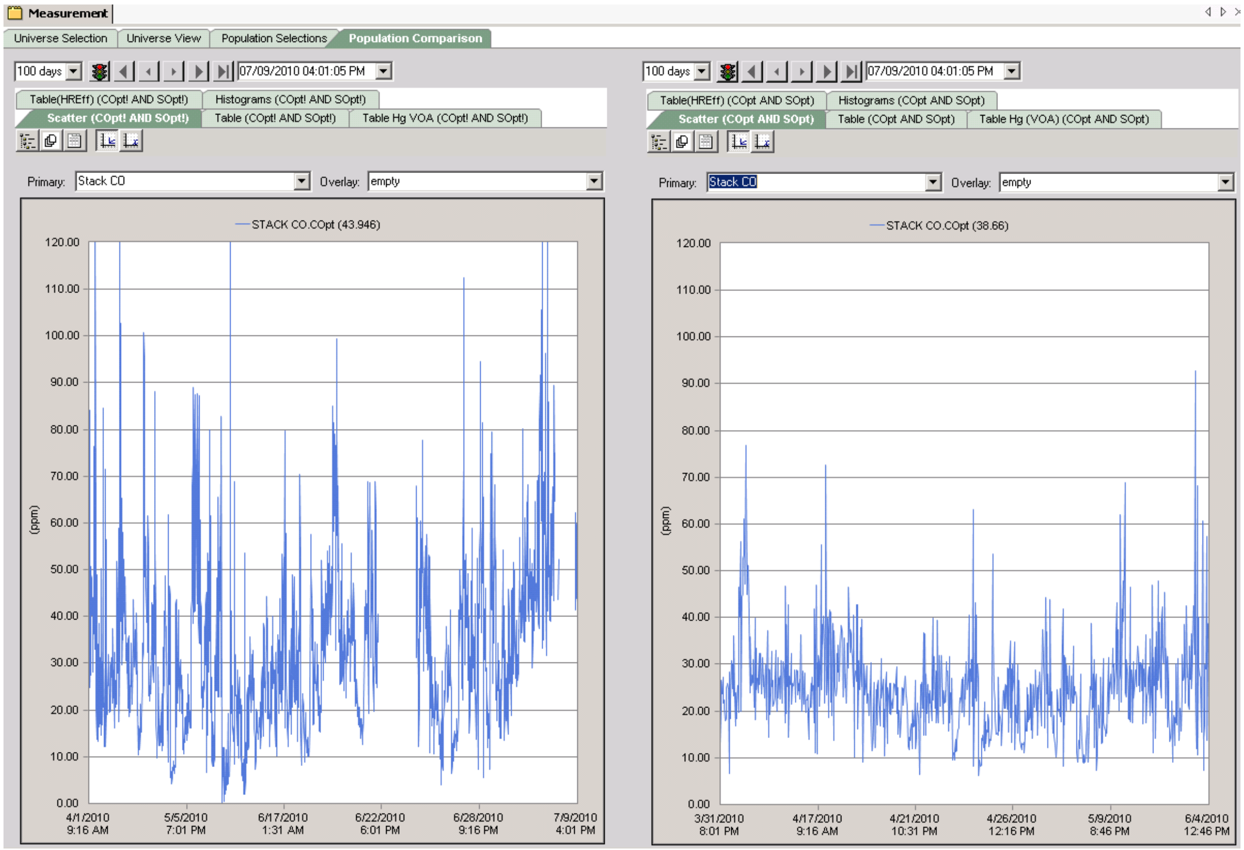

Figure 182: CEMS CO, MW>880, 3/31/10 - 7/9/10

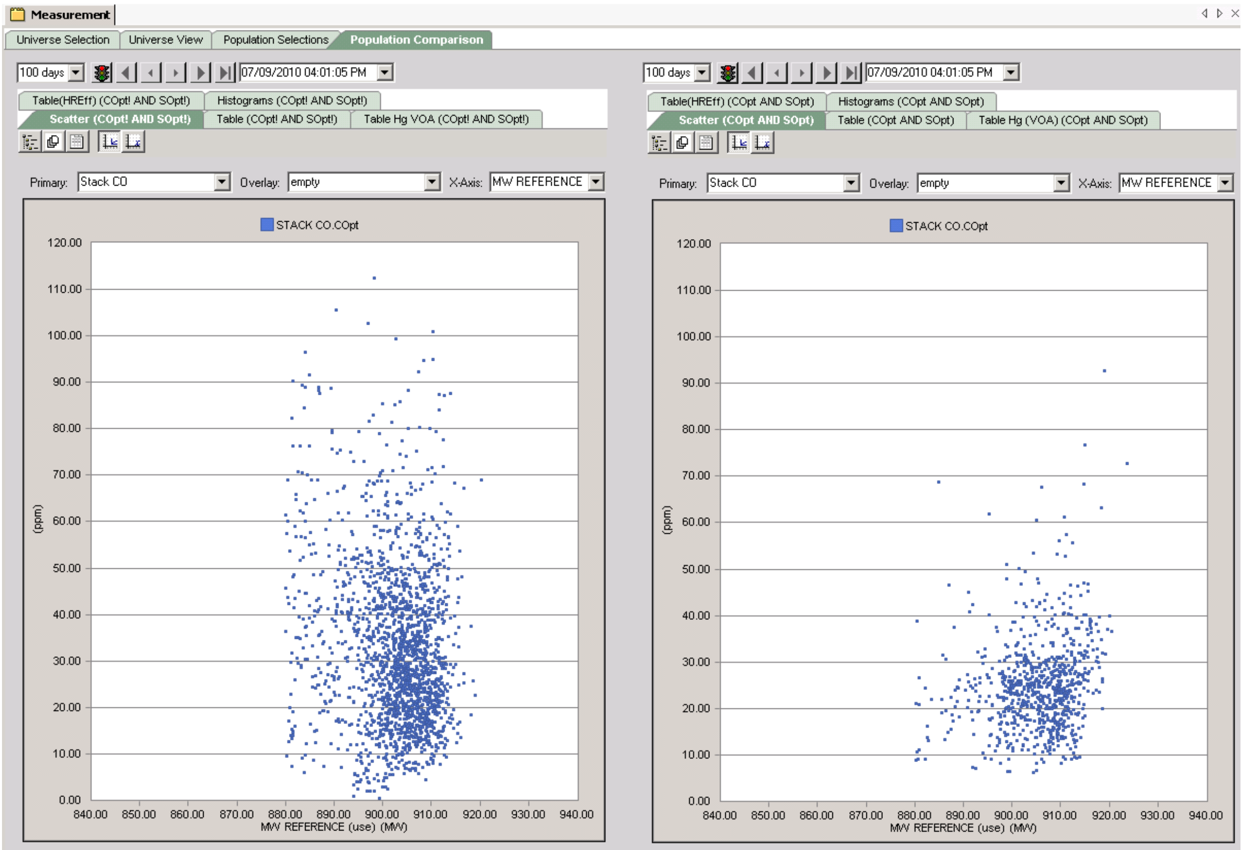

Figure 183: CEMS CO, MW>880, 3/31/10 - 7/9/10

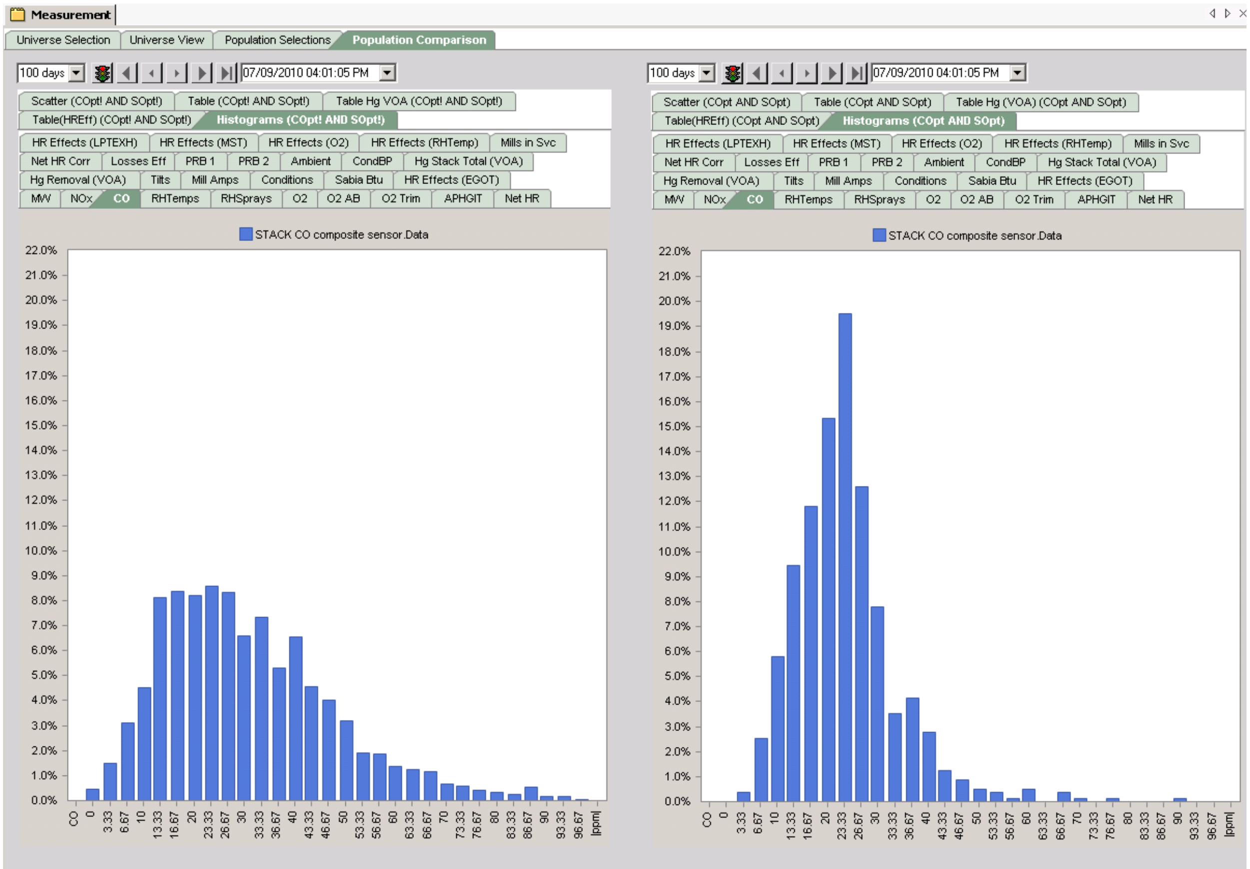

Figure 184: CEMS CO, MW>880, 3/31/10 - 7/9/10

3.6.6.7 Reheat Steam Temps

Reheat Steam temps (RH Temps) had both "maximum limit" and "minimum limit" objectives in the Optimization Profile, with the limit set to 1005 degF and 980 degF respectively. LMS U2 Unit 2 is typically constrained on low RH Temps, causing the operators to have to increase tilts. However, increasing tilts leads to higher NOx.

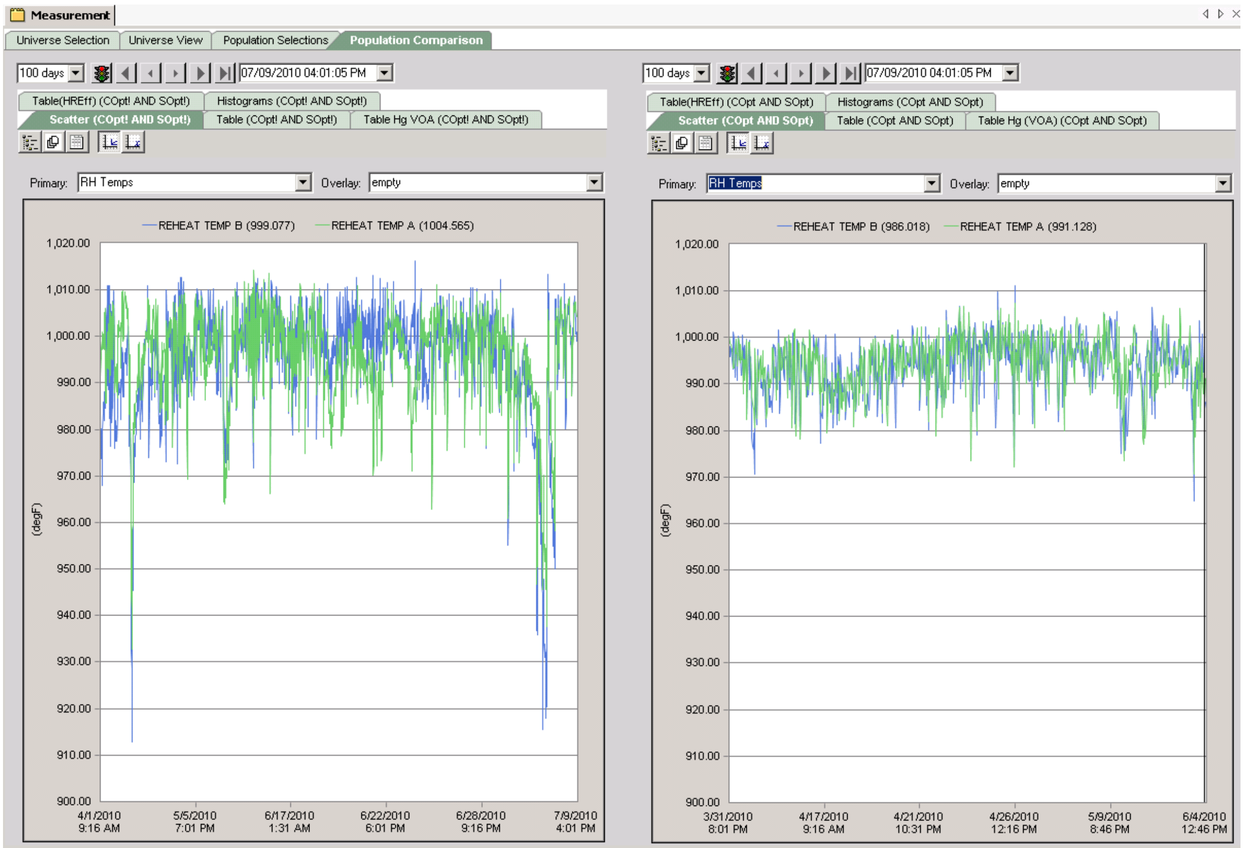

Figure 185: RH Temps, MW>880, 3/31/10 - 7/9/10

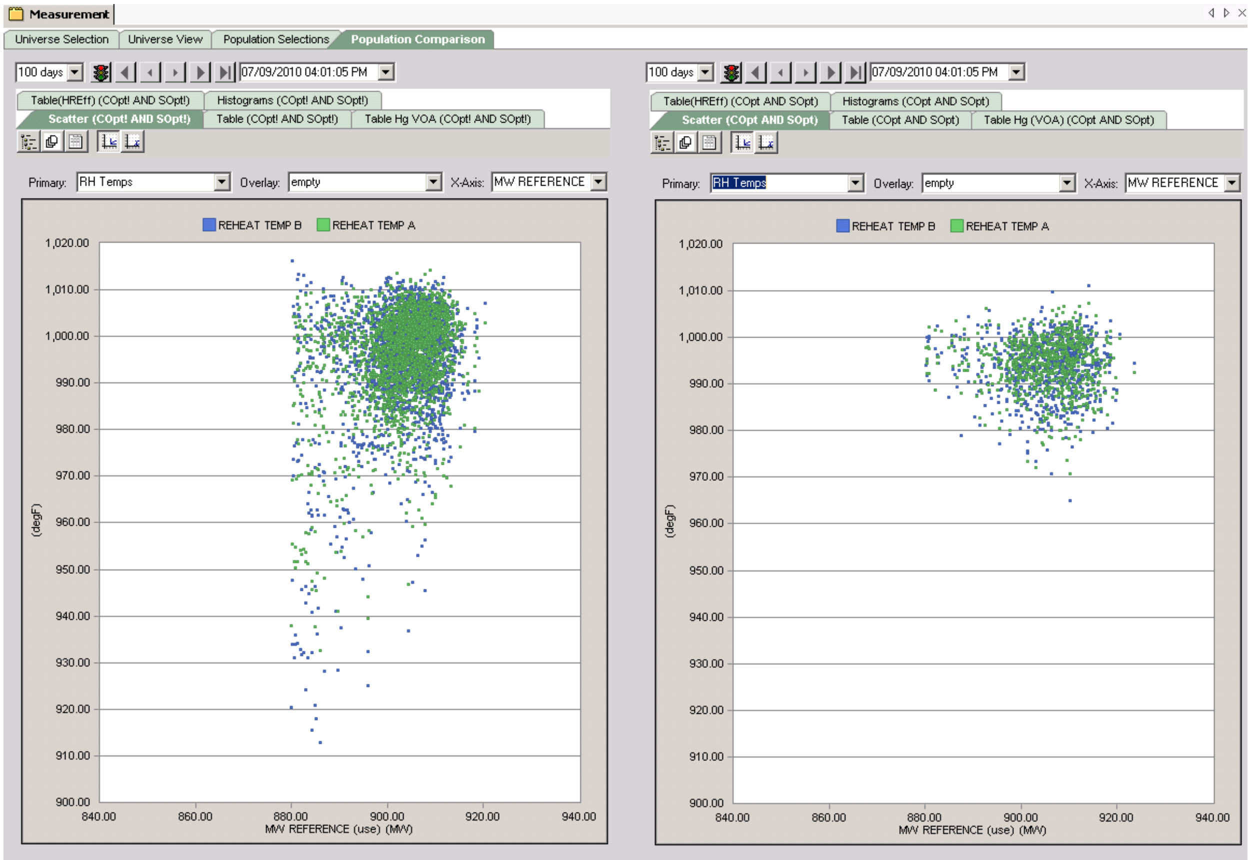

Figure 186: RH Temps, MW>880, 3/31/10 - 7/9/10

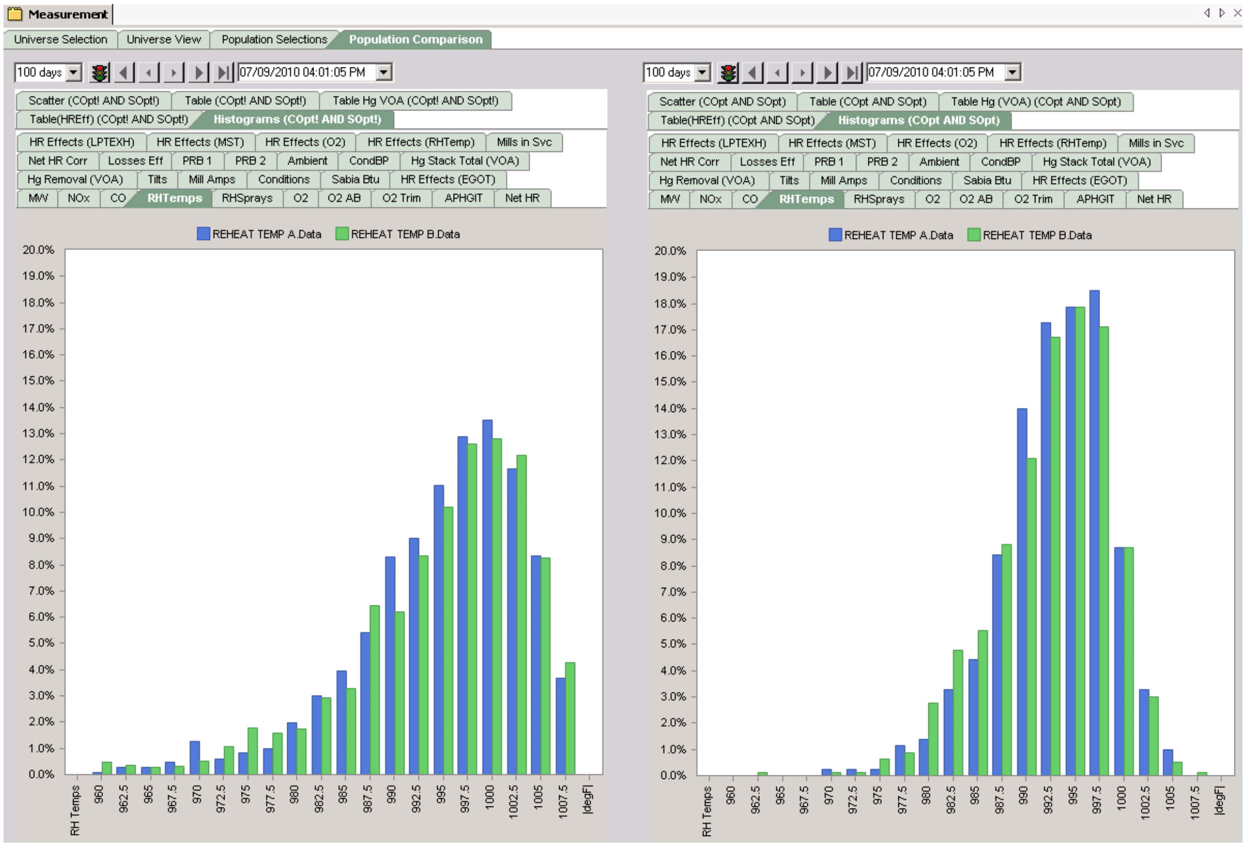

Figure 187: RH Temps, MW>880, 3/31/10 - 7/9/10

3.6.6.8 O2

There is currently a “minimum limit” objective of 2.0% for Boiler O2 as well as for A&B Side O2 variables. O2 showed more variability in the experimental population than the control population. Normally this would not be desirable but since O2 is the primary lever on the combustion process this is consistent with, and likely the cause of, the improvements in NOx and CO that was shown. The optimizer was lowering O2 as it has to in order to get NOx down, but raising it when it needed to in order to respond to CO. The low limit on the O2 measure itself does not play a significant role in limiting optimizer behavior since the CO response kicks in well above that limit. This demonstrates the importance of having CO instrumentation.

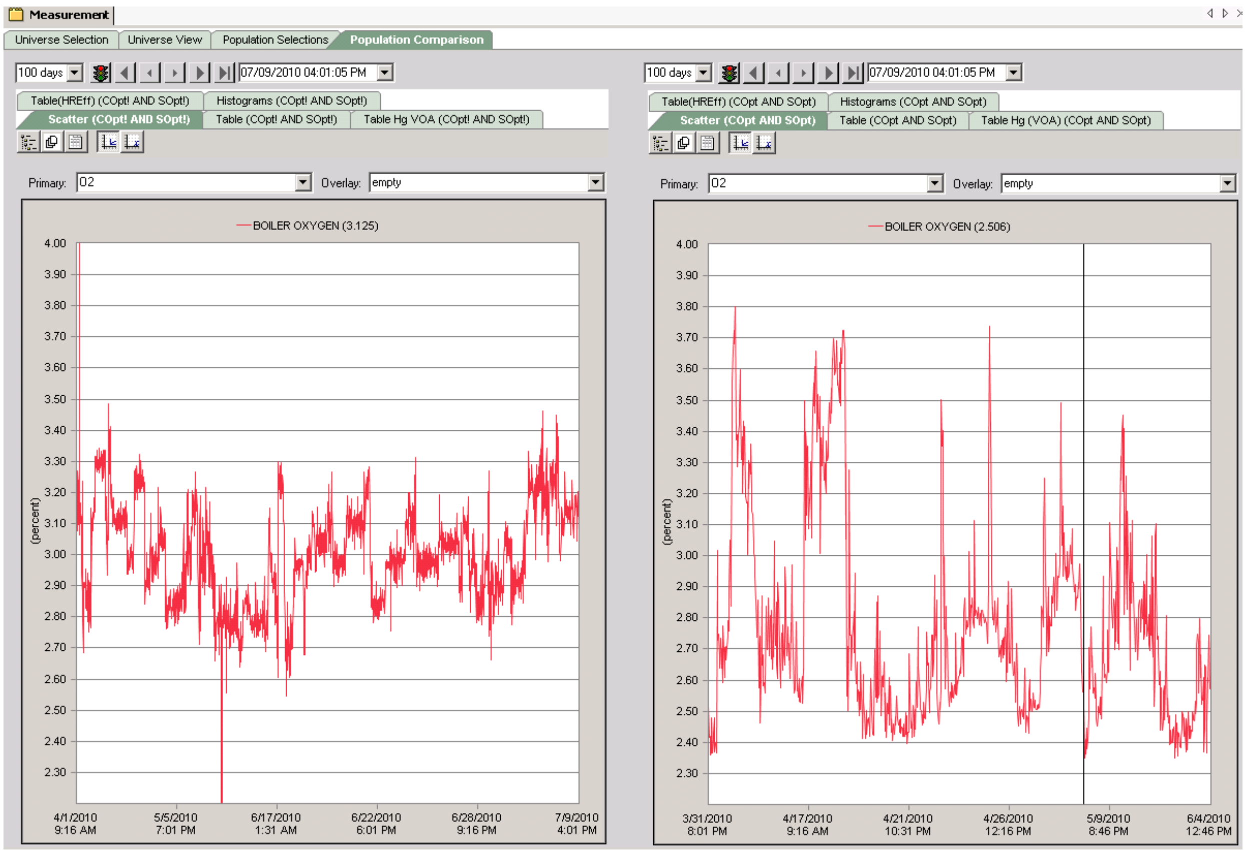

Figure 188: Boiler O2, MW>880, 3/31/10 - 7/09/10

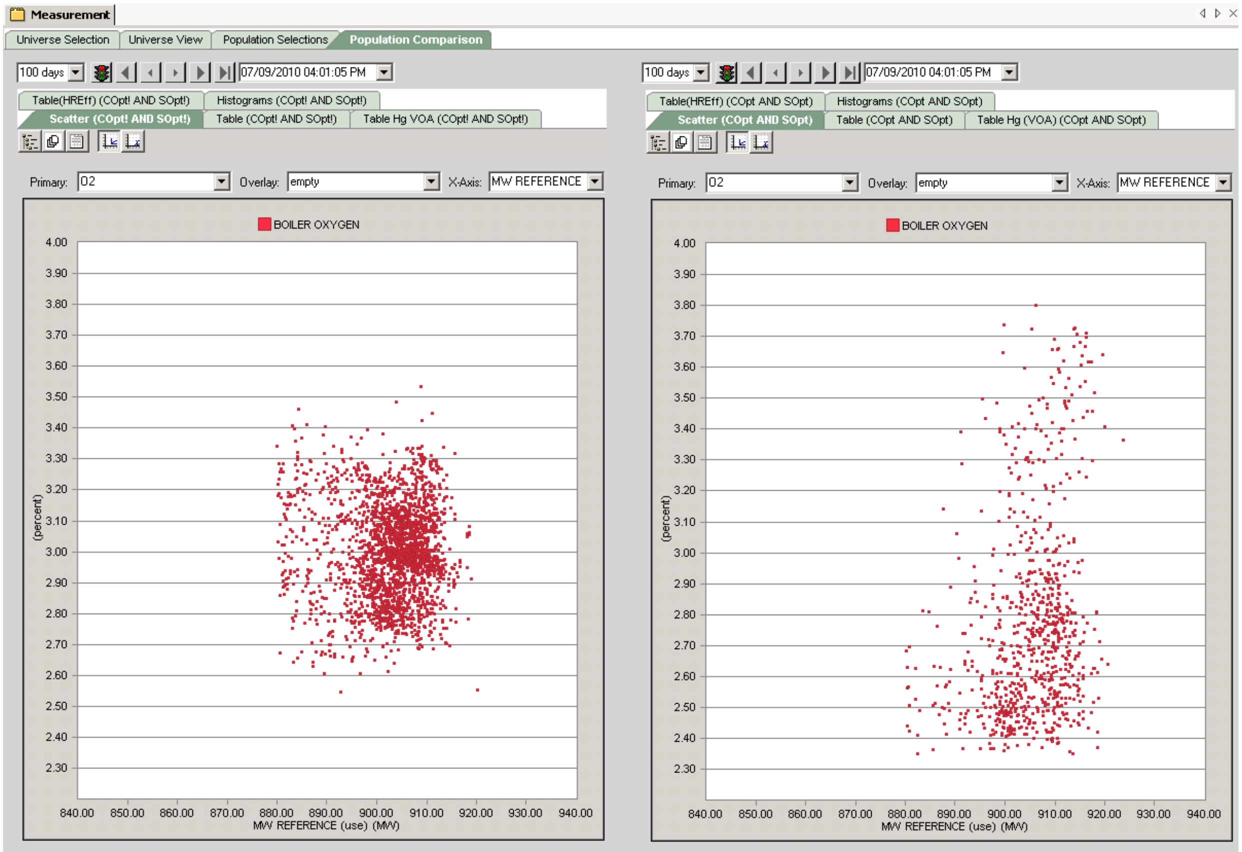

Figure 189: Boiler O2, MW>880, 3/31/10 - 7/09/10

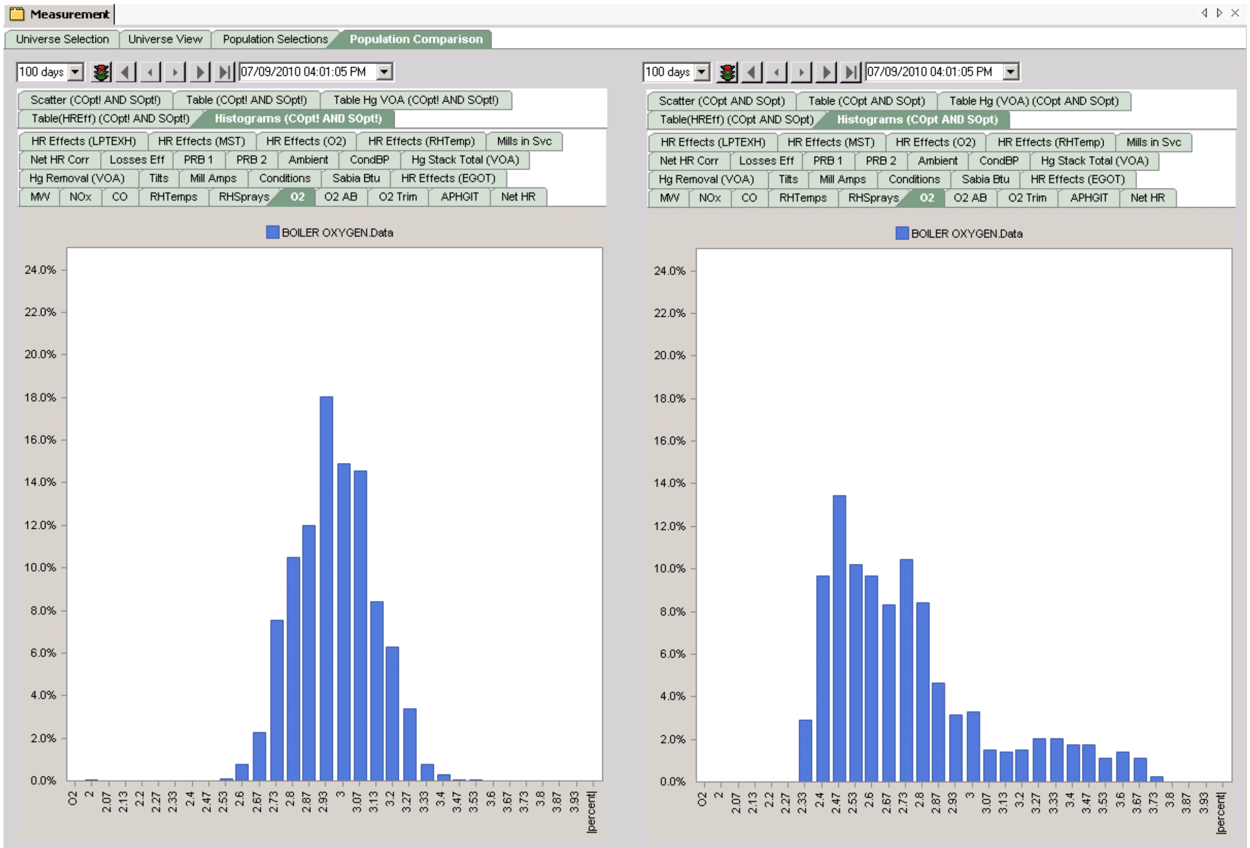

Figure 190: Boiler O2, MW>880, 3/31/10 - 7/09/10

Figure 191: O2Trim, MW>880, 3/31/10 - 7/9/10

3.6.6.9 A and B Side O2

The A and B Side O2 probes, while above their objective limit also showed more variability. O2 Trim is a single manipulated variable that affects both sides of the split t-fired unit equally by adding demand to the fan system that supplies secondary air to both furnaces. However in addition to the O2 Trim, the optimizer could use over fired air dampers (called SSAS dampers on LMS U2) as well as burner auxiliary air dampers (Aux Dampers) both of which have separate MV's for each side furnace.

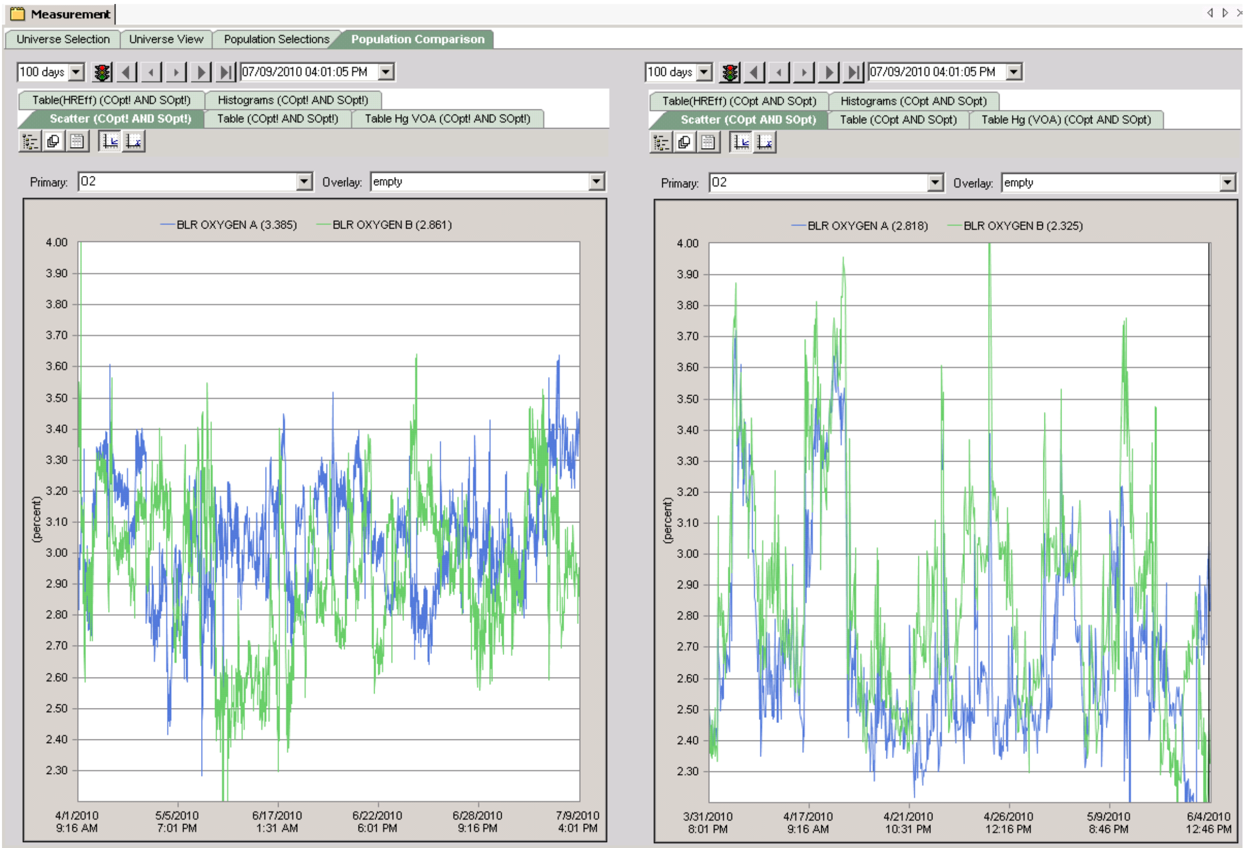

Figure 192: A&B Side O2, MW>880, 3/31/10 - 7/9/10

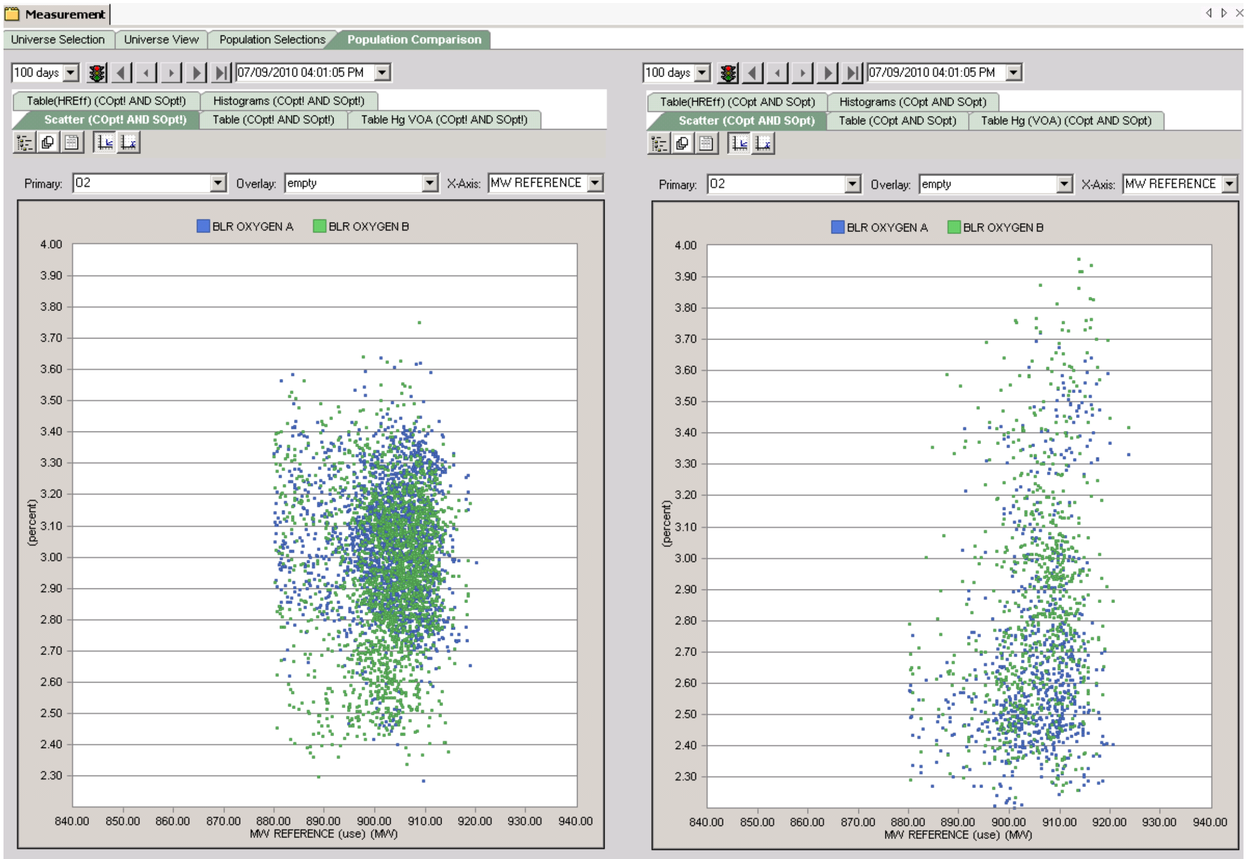

Figure 193: A&B Side O2, MW>880, 3/31/10 - 7/9/10

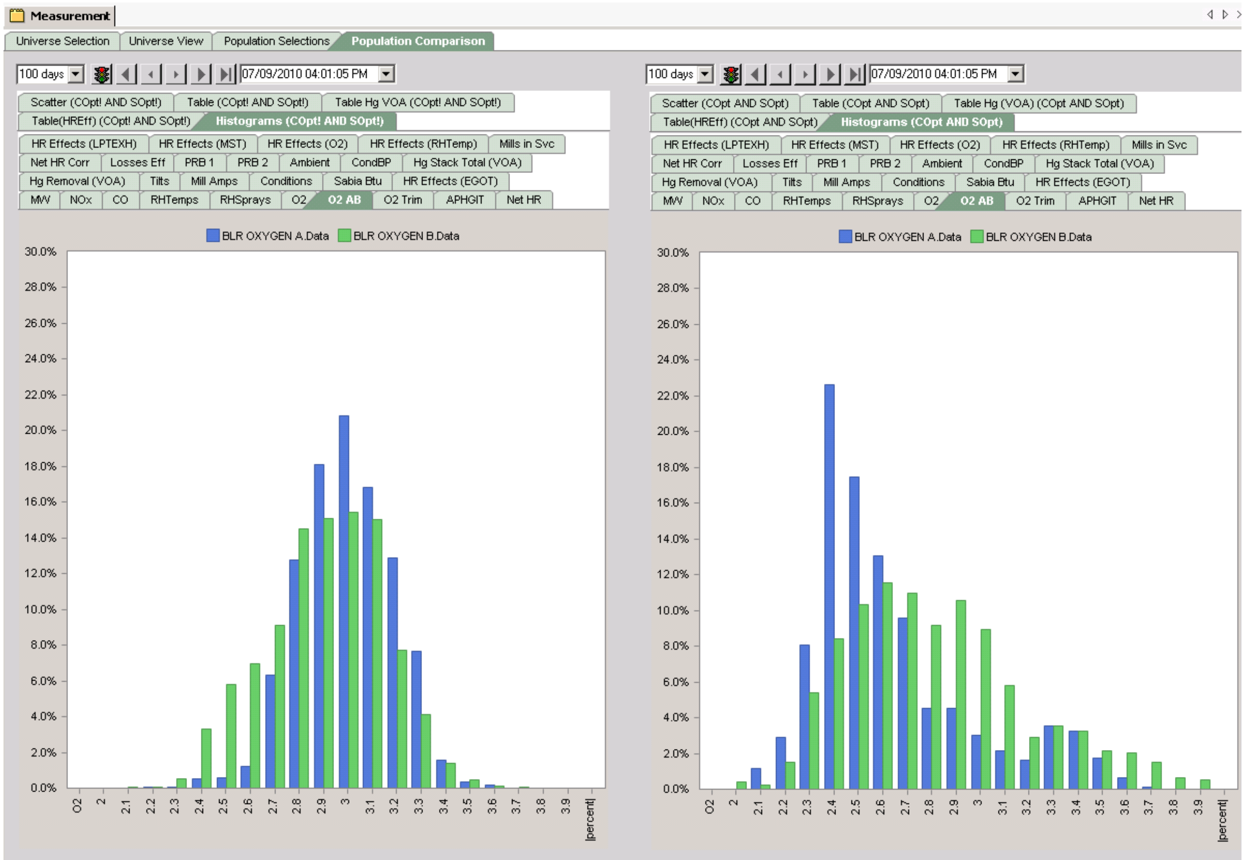

Figure 194: A&B Side O2, MW>880, 3/31/10 - 7/9/10

3.6.6.10 Optimization MV Activity

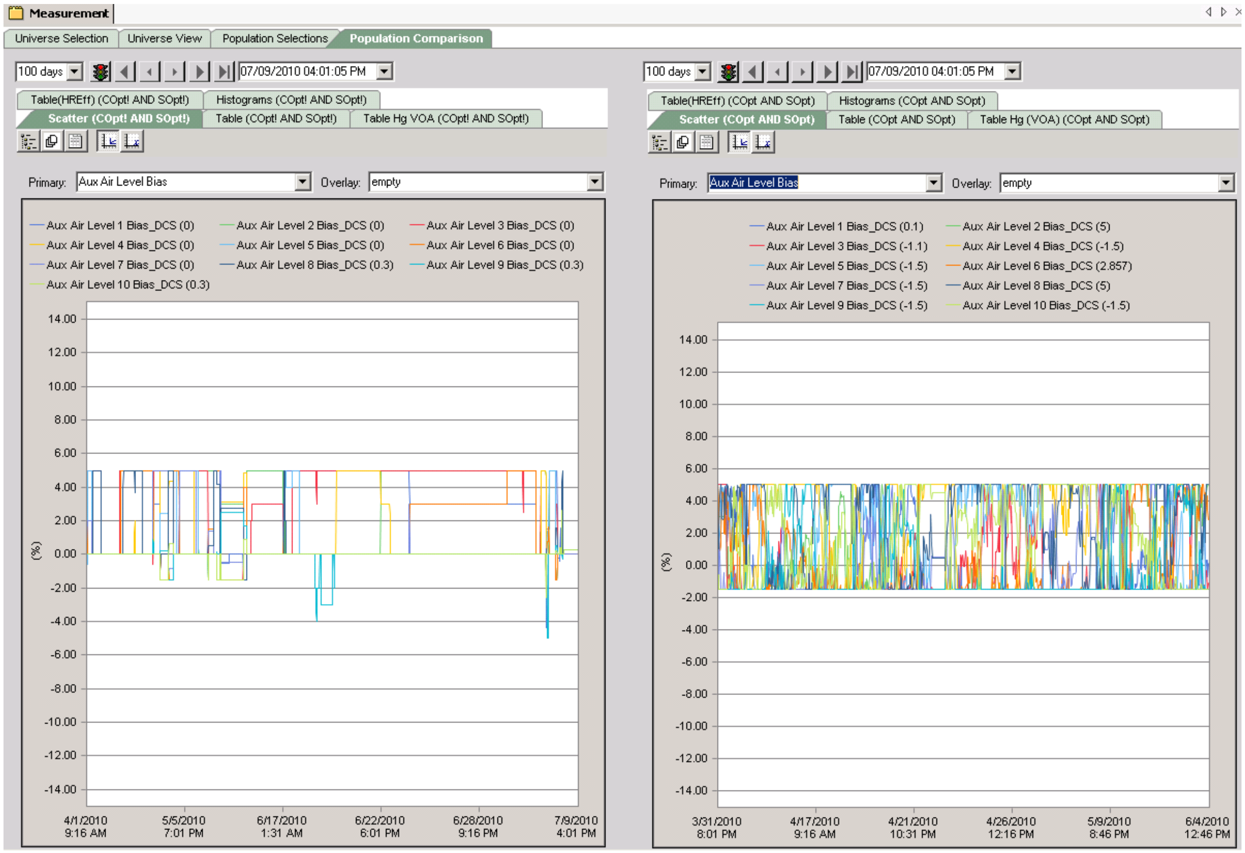

Figure 195: Aux Air Damper Biases, MW>880, 3/31/10-7/9/10

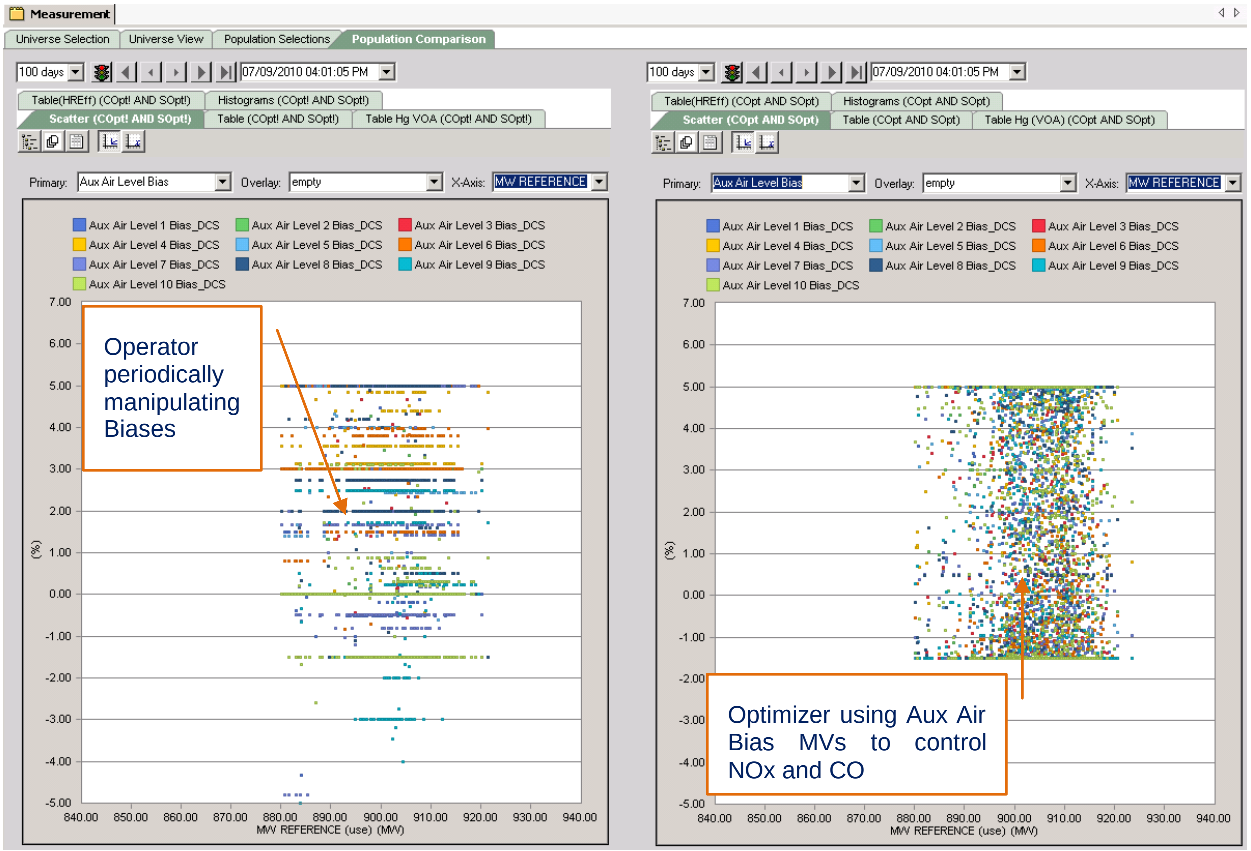

Figure 196: Aux Air Damper Biases, MW>880, 3/31/10-7/9/10

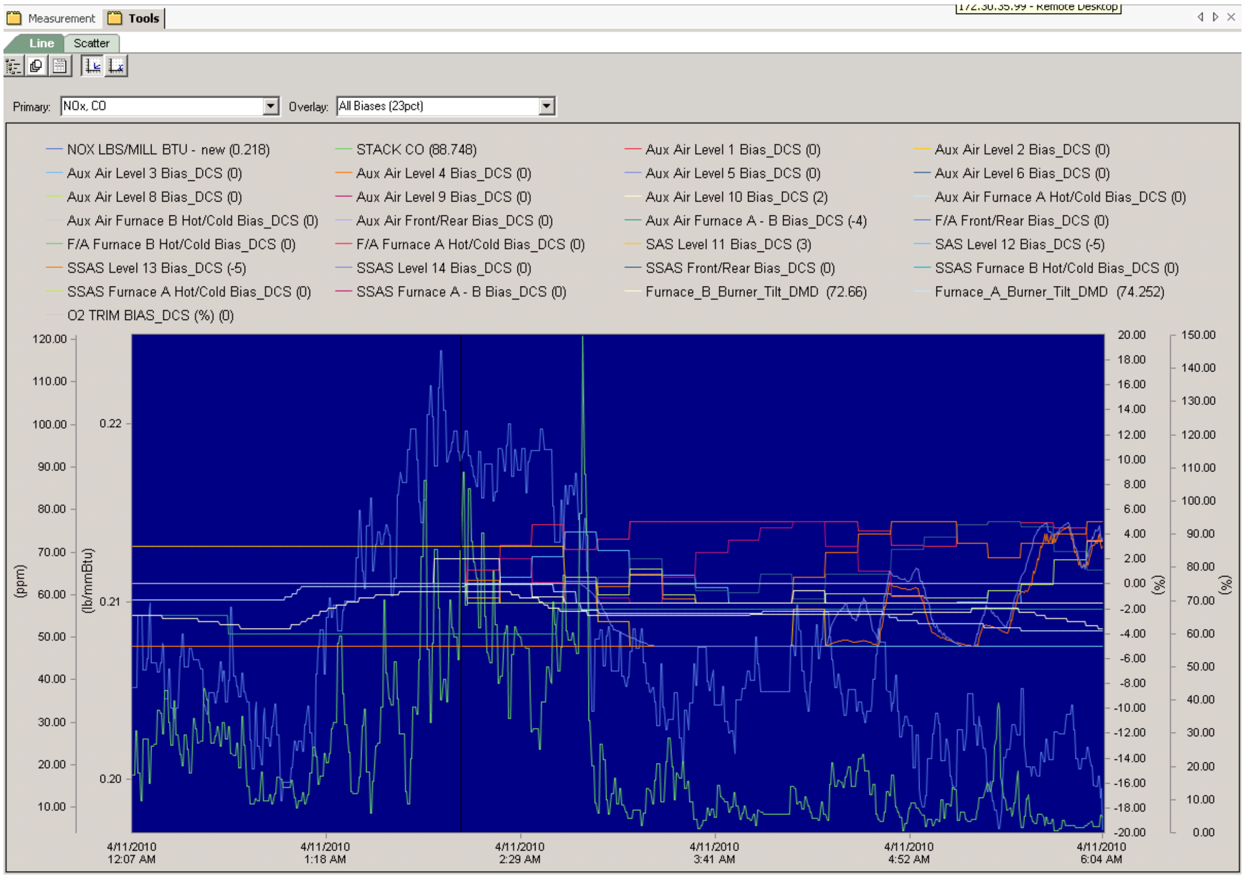

Figure 197: Engaging Optimization MV's

3.6.6.11 KPI’s vs Utilization Index

3.6.6.11.1 Hg Removal (VOA) vs Utilization Index

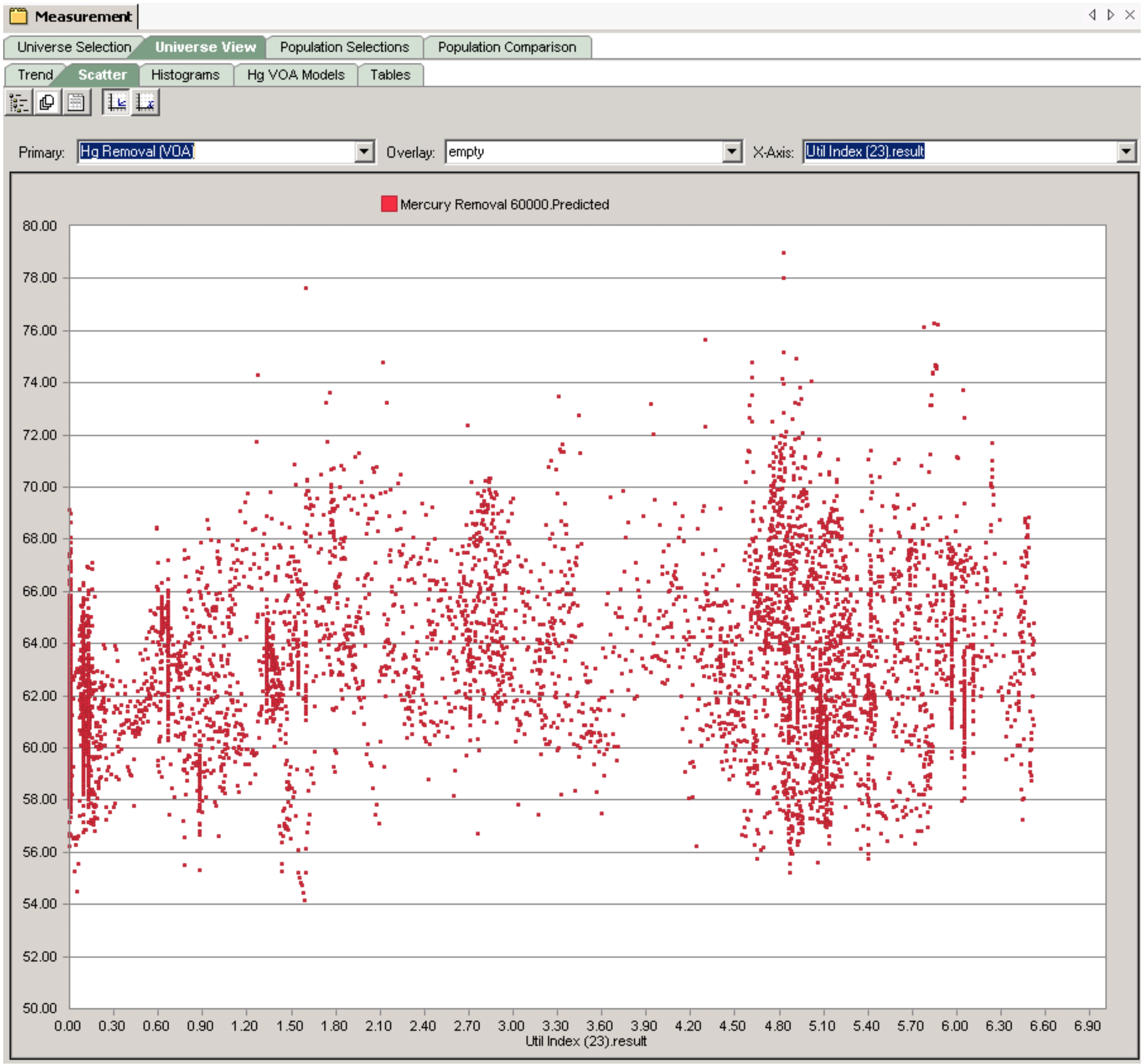

Figure 198: Hg Removal (VOA) vs Utilization Index

This is based on 23 MV's tested so far (23% of total MVs available)

3.6.6.11.2 Mercury Stack Total vs Utilization Index

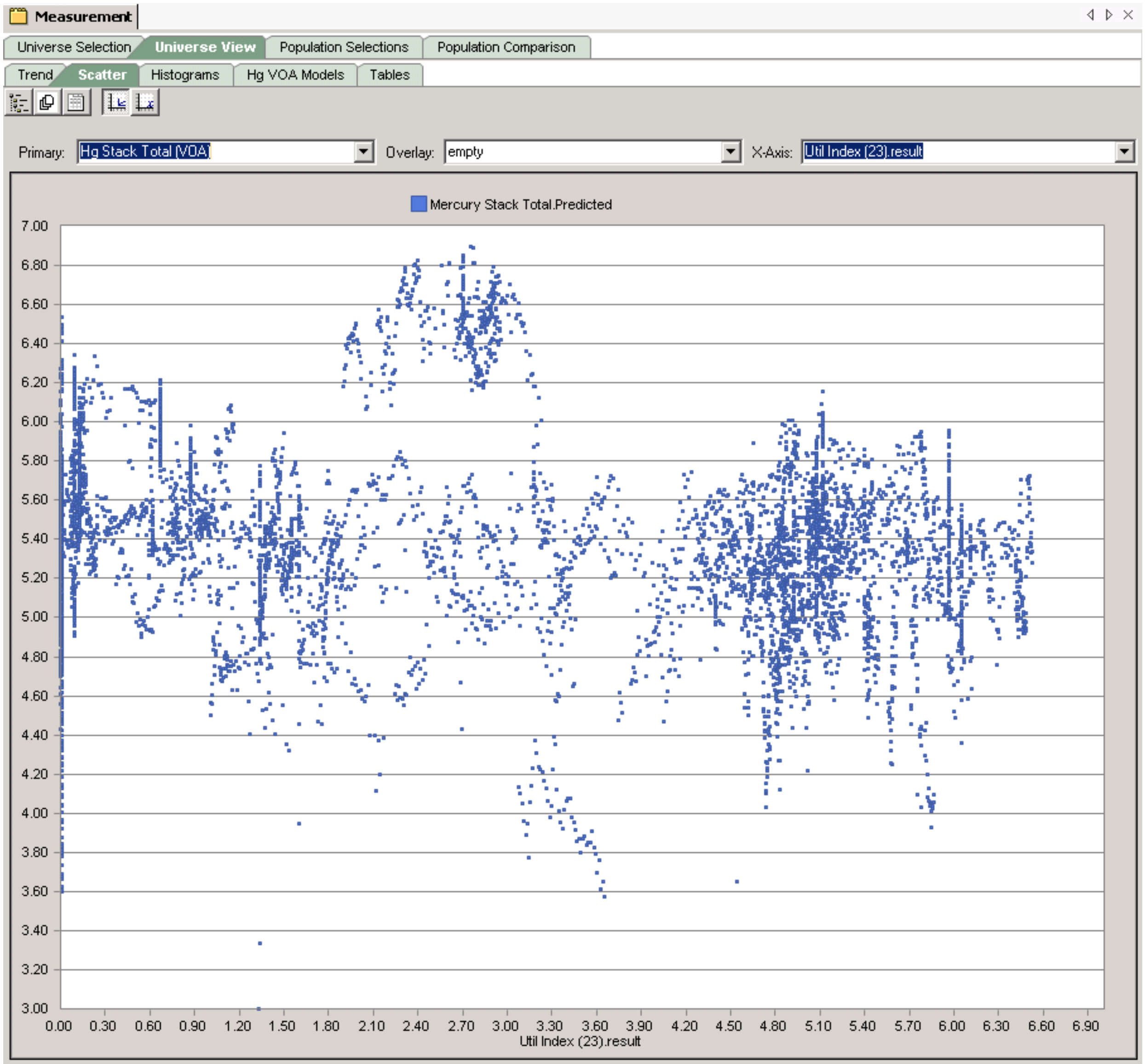

Figure 199: Hg Stack Total (VOA) vs Utilization Index

This is based on 23 MV's tested so far (23% of total MVs available)

3.6.6.11.3 CEMS NOx vs Utilization Index

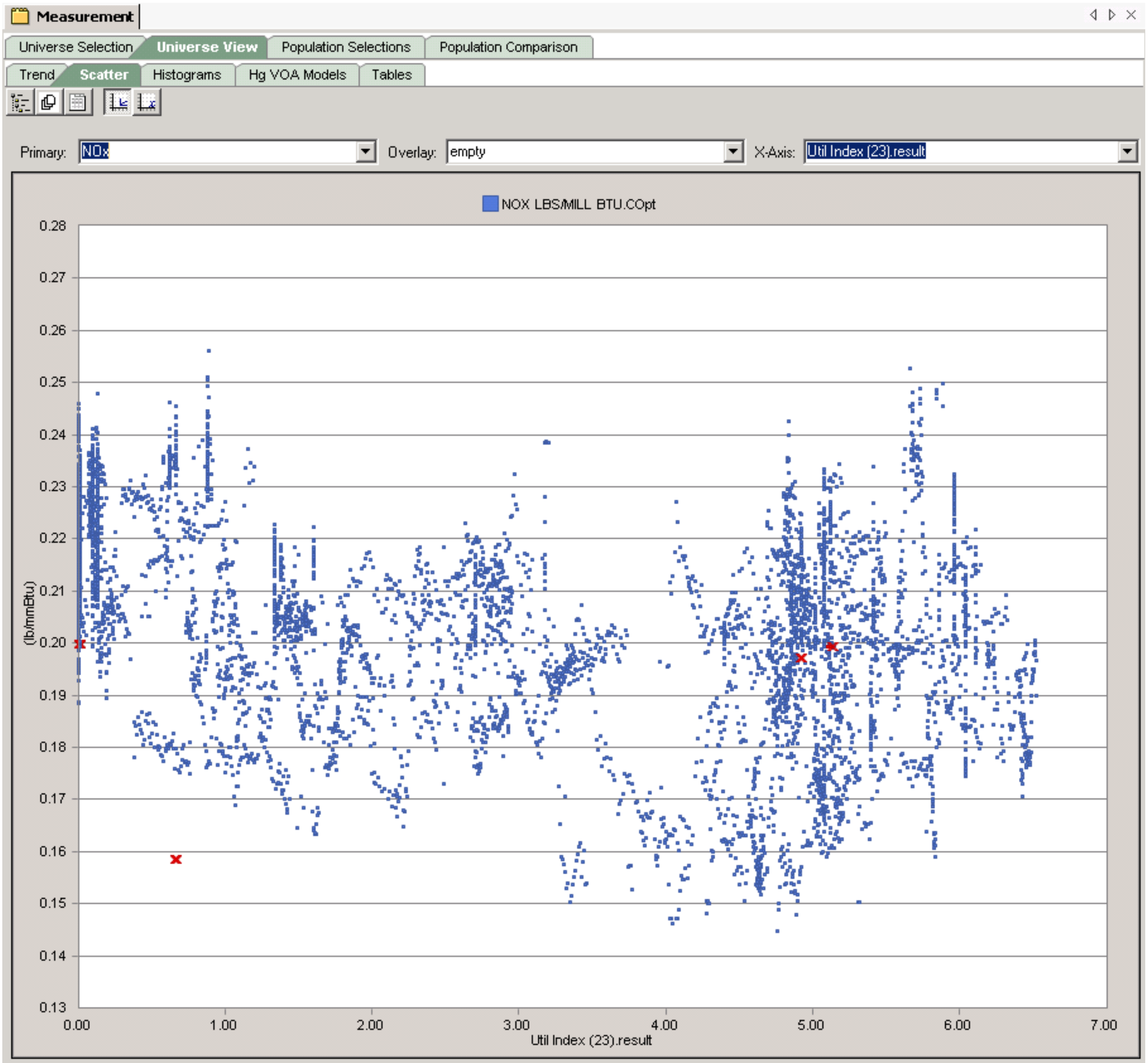

Figure 200: NOx vs. Utilization Index

This is based on 23 MV's tested so far (23% of total MVs available)

3.6.6.11.4 CEMS CO vs Utilization Index

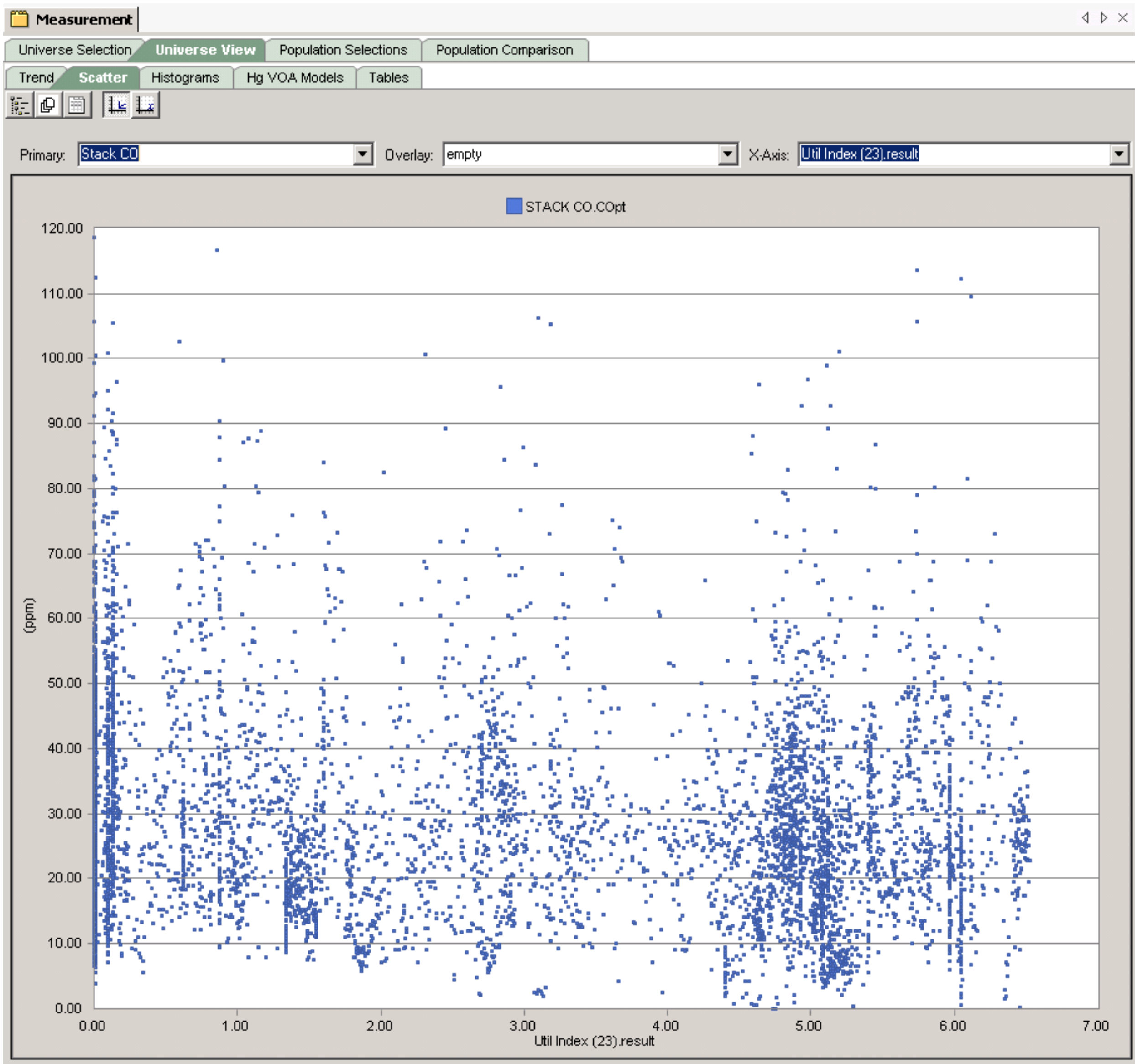

Figure 201: CO vs. Utilization Index

This is based on 23 MV's tested so far (23% of total MVs available)

3.6.6.12 Burner Tilt Demand

Burner Tilt Demand was a manipulated variable for the model predictive controller (MPC) and an objective for the neural net model based optimizer. CombustionOpt's neural optimizer cannot directly touch the Tilt Demand MV, but what it does with the variables it does touch directly affects the combustion and heat transfer processes in a way that can provide MPC with more or less freedom to do what it needs to do with the tilts. SootOpt's activity has a direct effect on Tilts position since it directs sootblowing in the convective heat transfer region of the boiler.

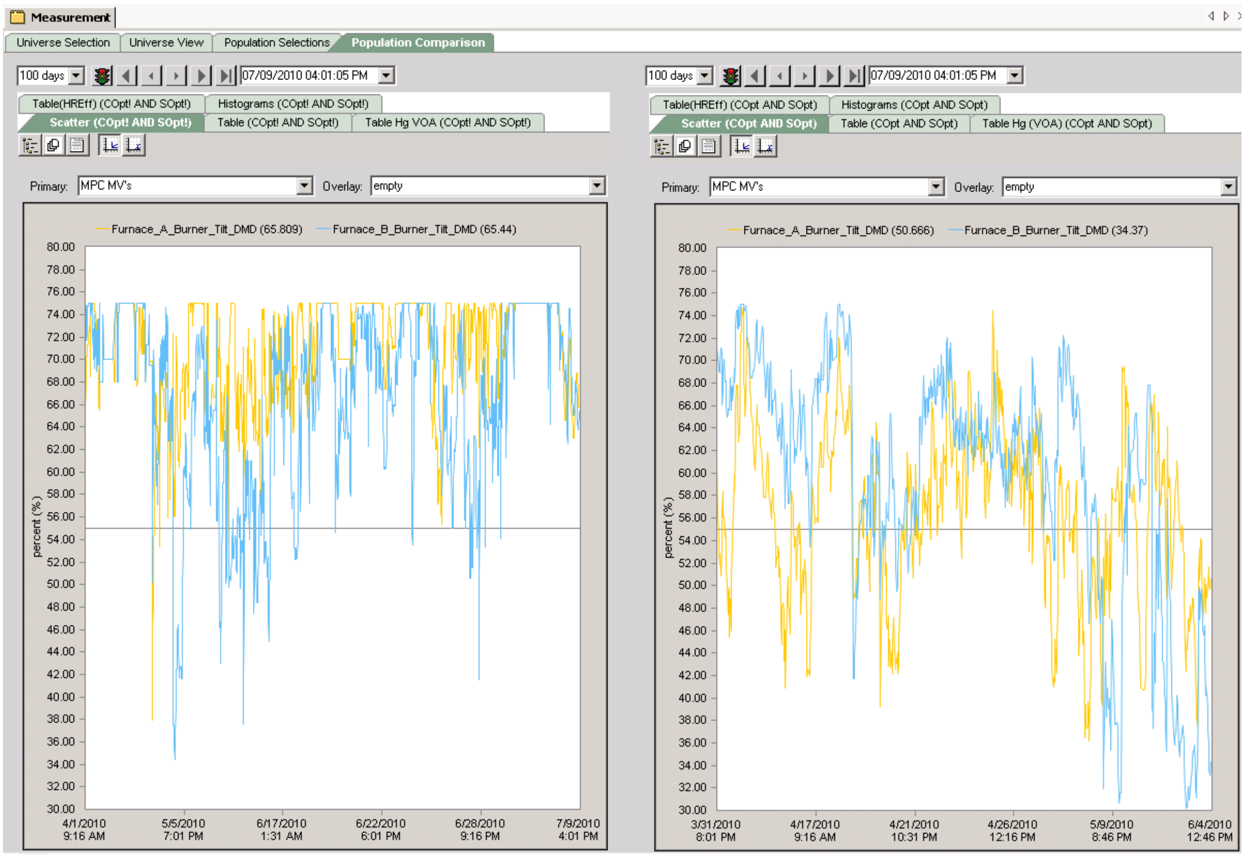

Figure 202: Burner Tilt Demand, MW>880, 3/1/10 - 7/9/10

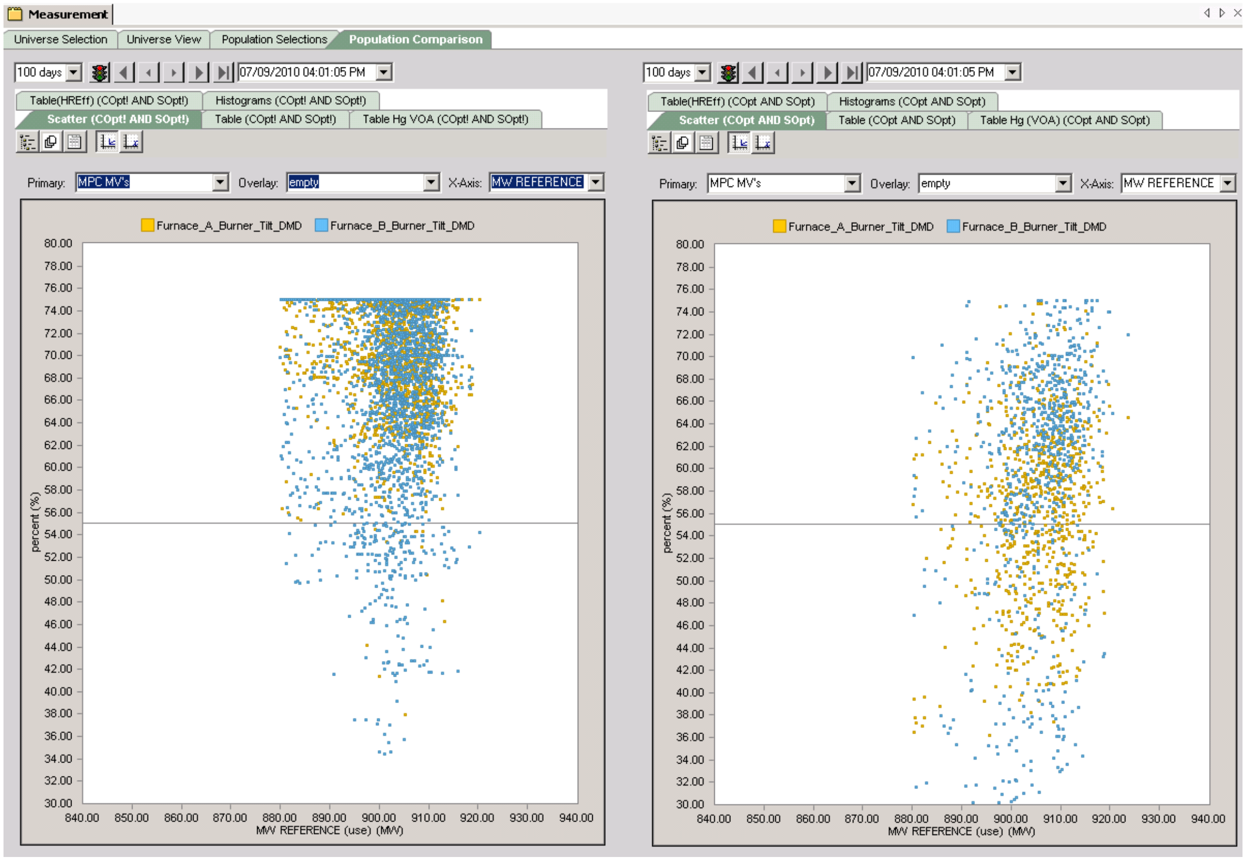

Figure 203: Burner Tilt Dmd, MW>880, 3/1/10 - 7/9/10

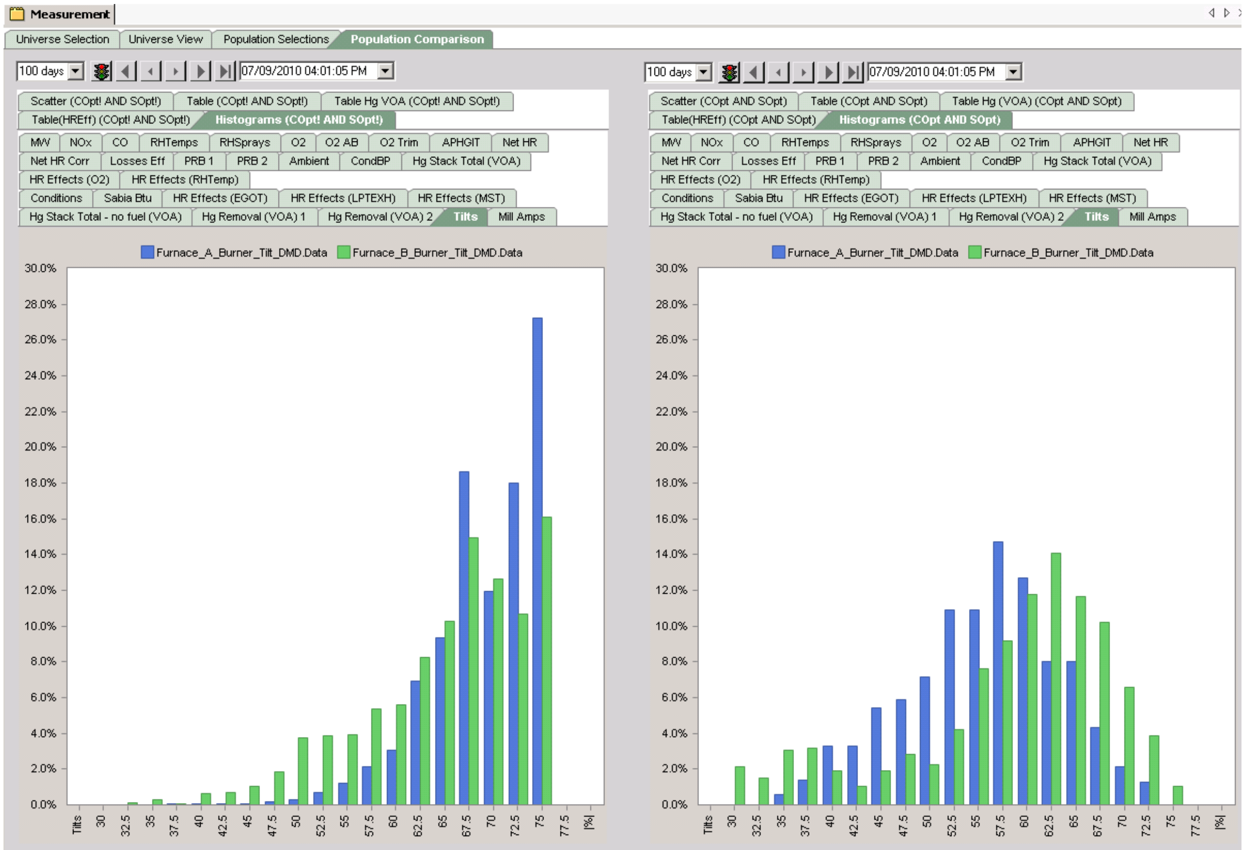

Figure 204: Burner Tilt Dmd, MW>880, 3/1/10 - 7/9/10

3.6.6.13 Air Preheater Gas Inlet Temp (APHGIT)/ Economizer Gas Outlet Temp

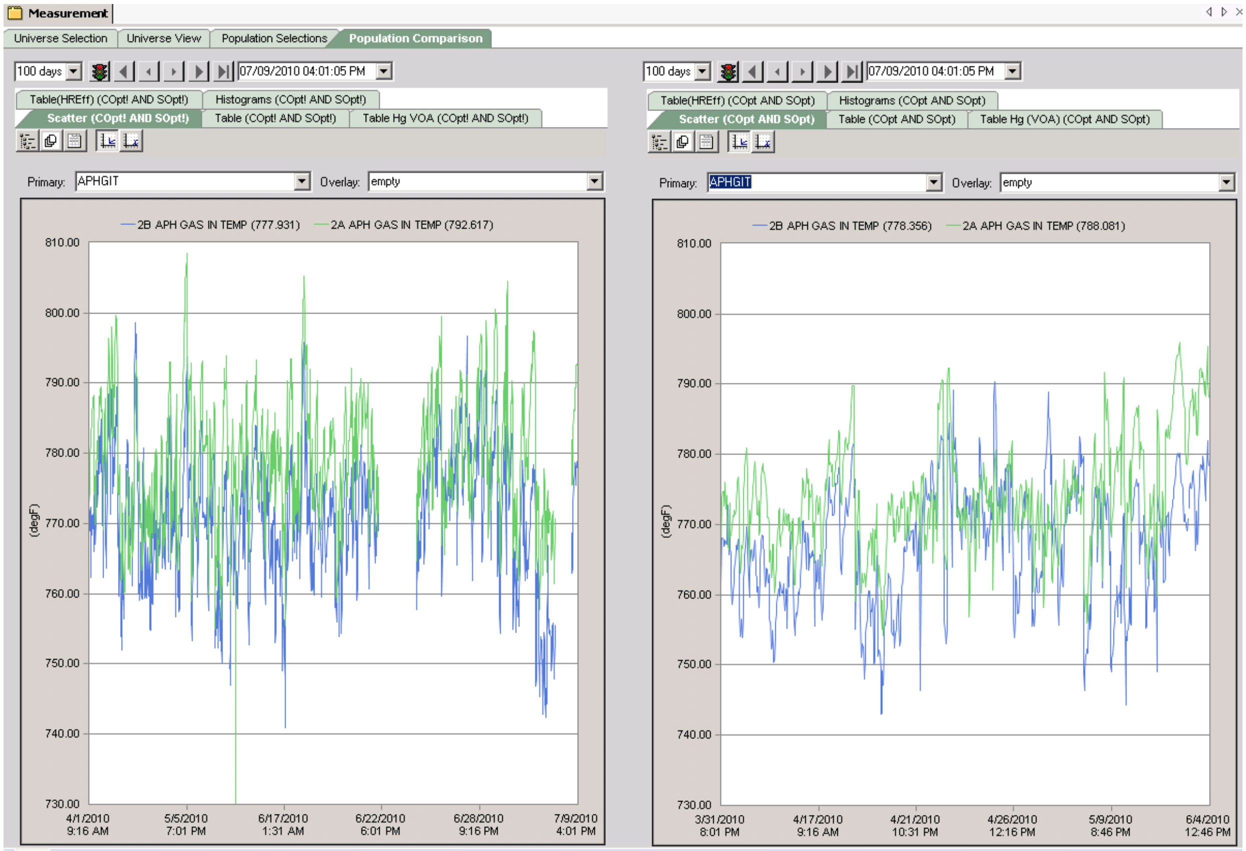

Figure 205: APHGIT, MW>880, 3/31/10 - 7/9/10

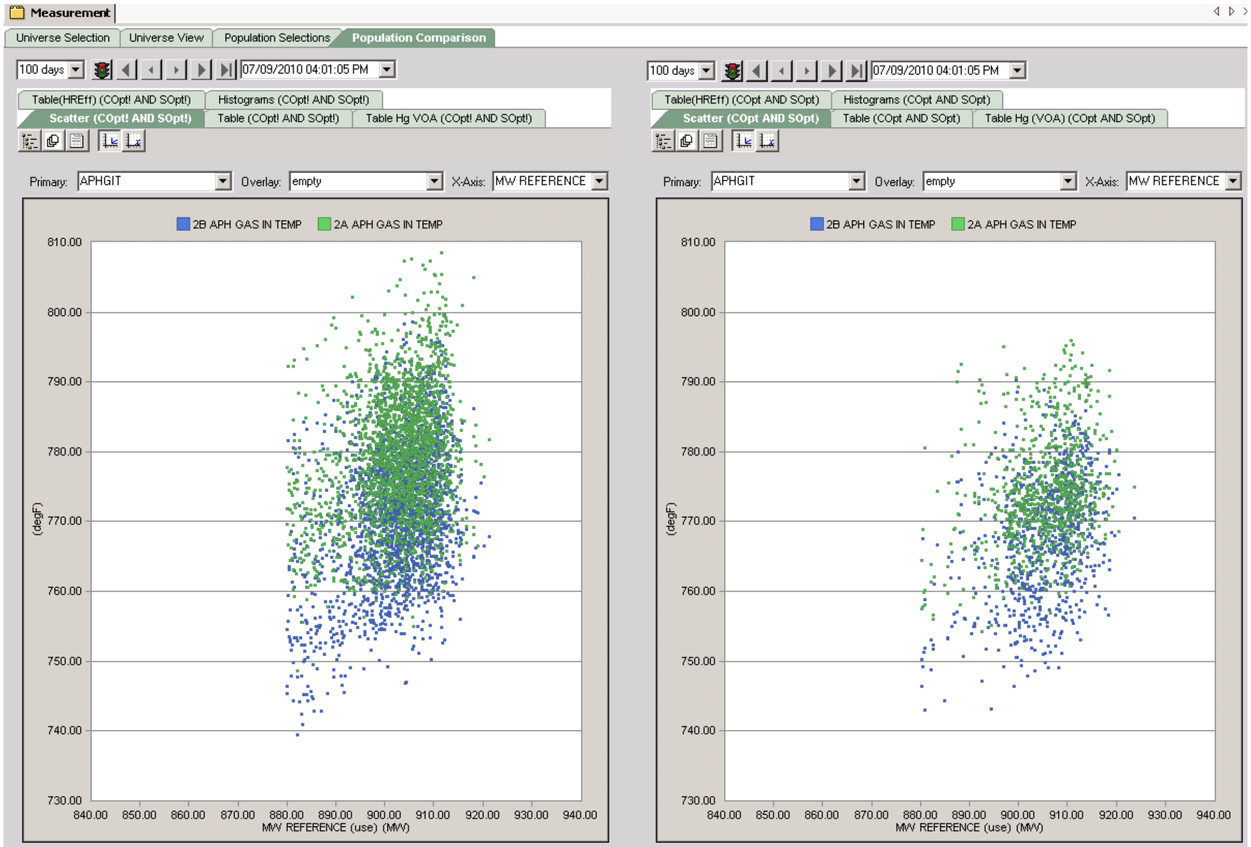

Figure 206: APHGIT, MW>880, 3/31/10 - 7/9/10

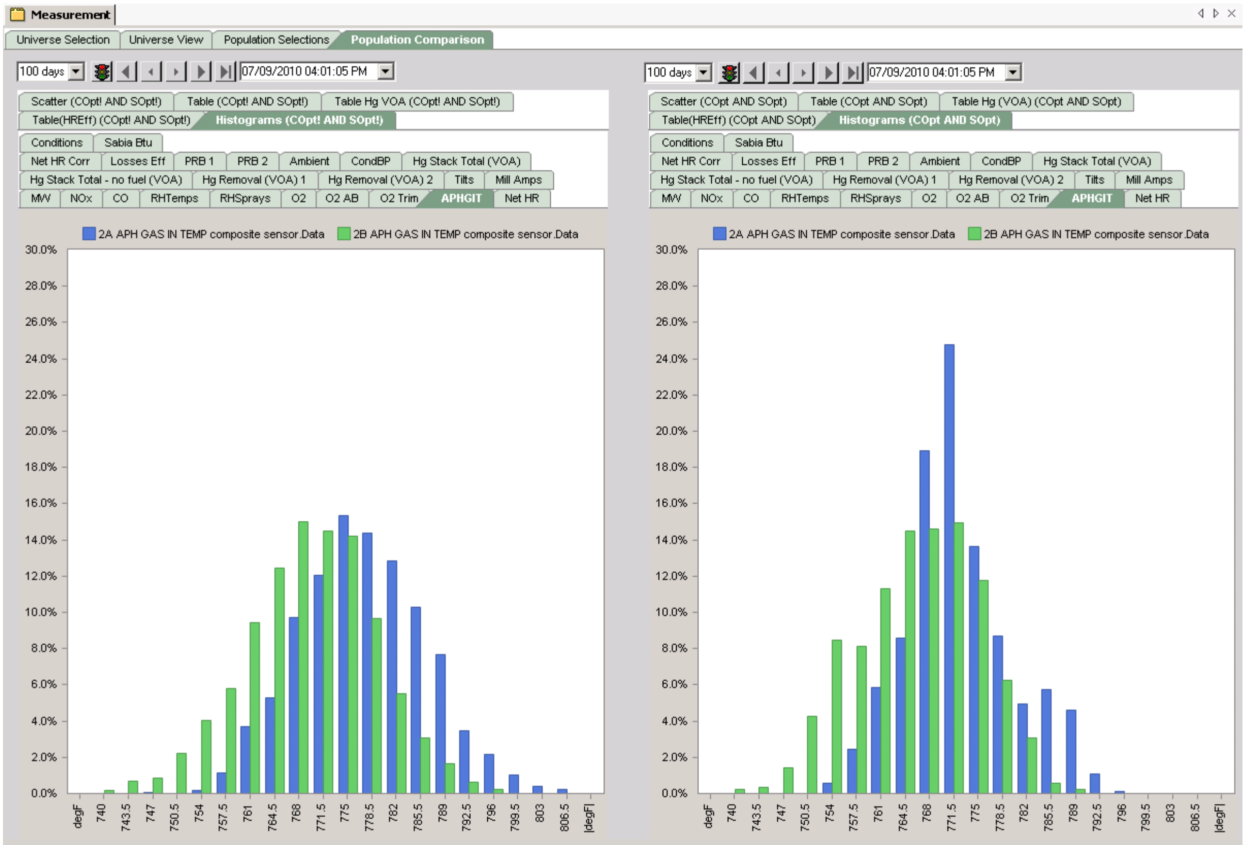

Figure 207: APHGIT, MW>880, 3/31/10 - 7/9/10

3.6.6.14 Net Unit Heat Rate

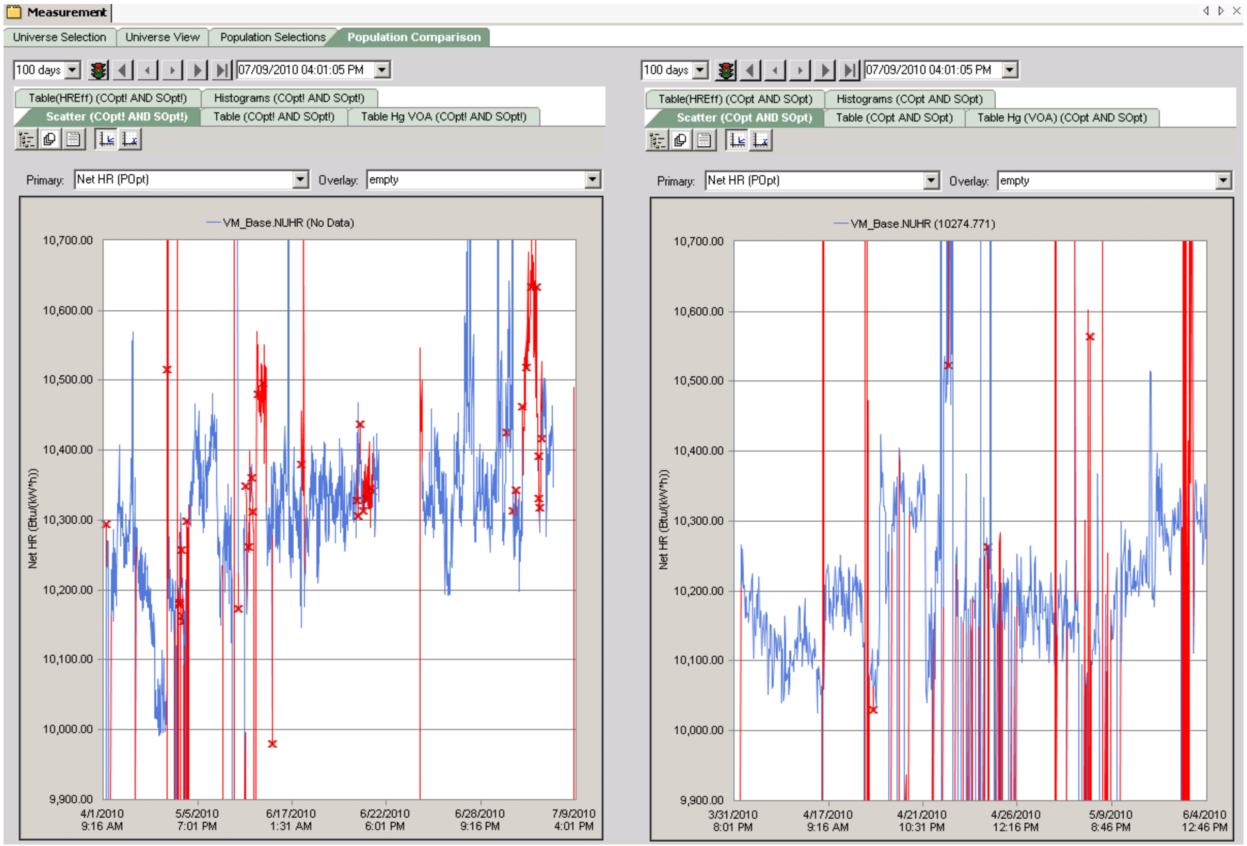

Figure 208: PerformanceOpt Net Unit Heat Rate, MW>880, 3/31/10 - 7/9/10

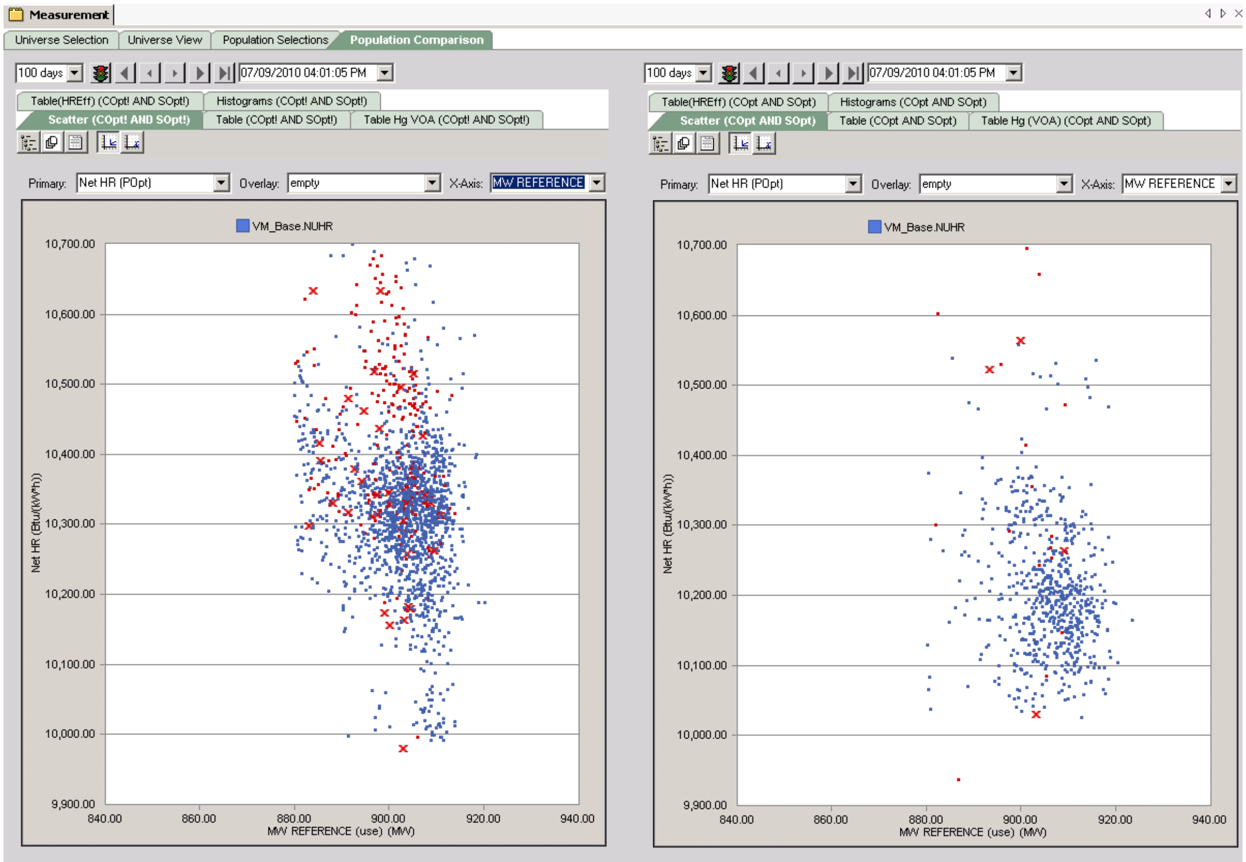

Figure 209: PerformanceOpt Net Unit Heat Rate, MW>880, 3/31/10 - 7/9/10

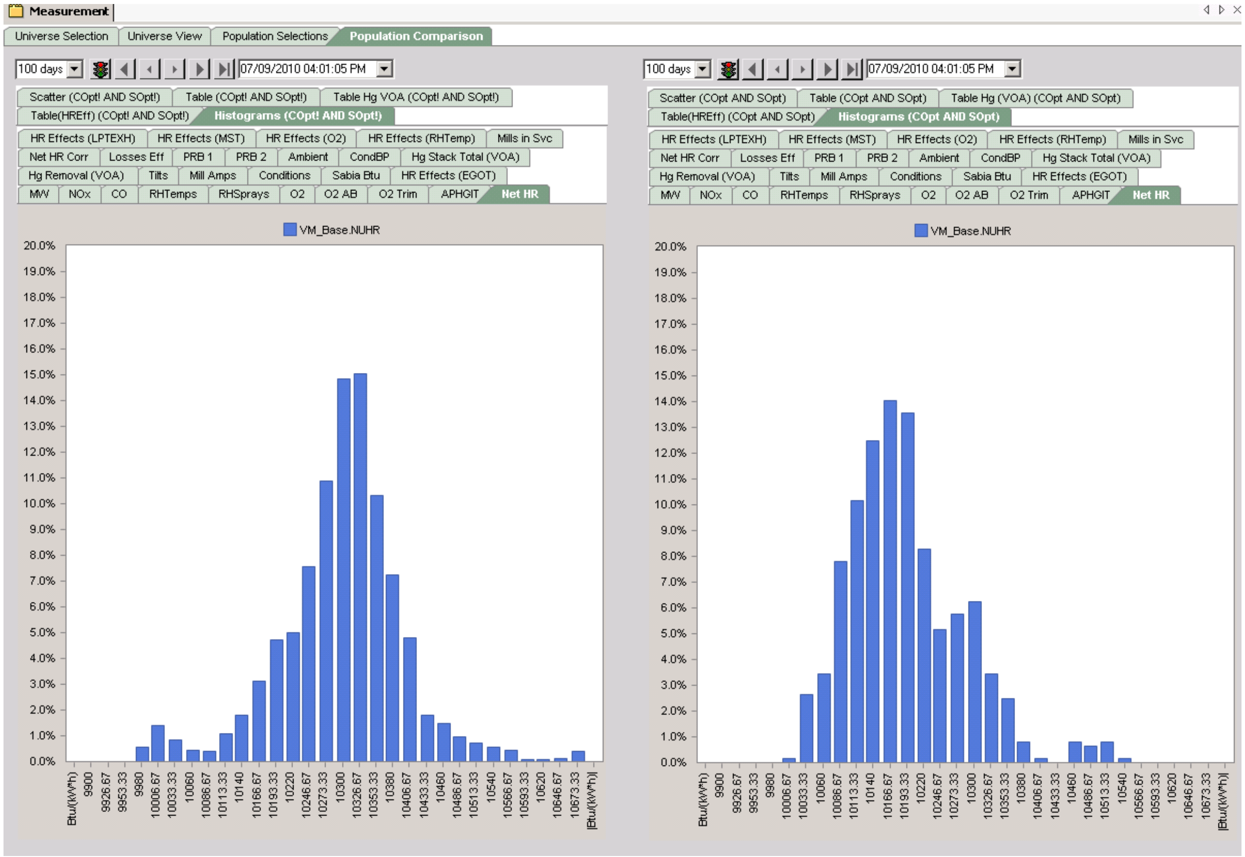

Figure 210: PerformanceOpt Net Unit Heat Rate, MW>880, 3/31/10 - 7/9/10

3.6.6.15 Net Turbine Heat Rate

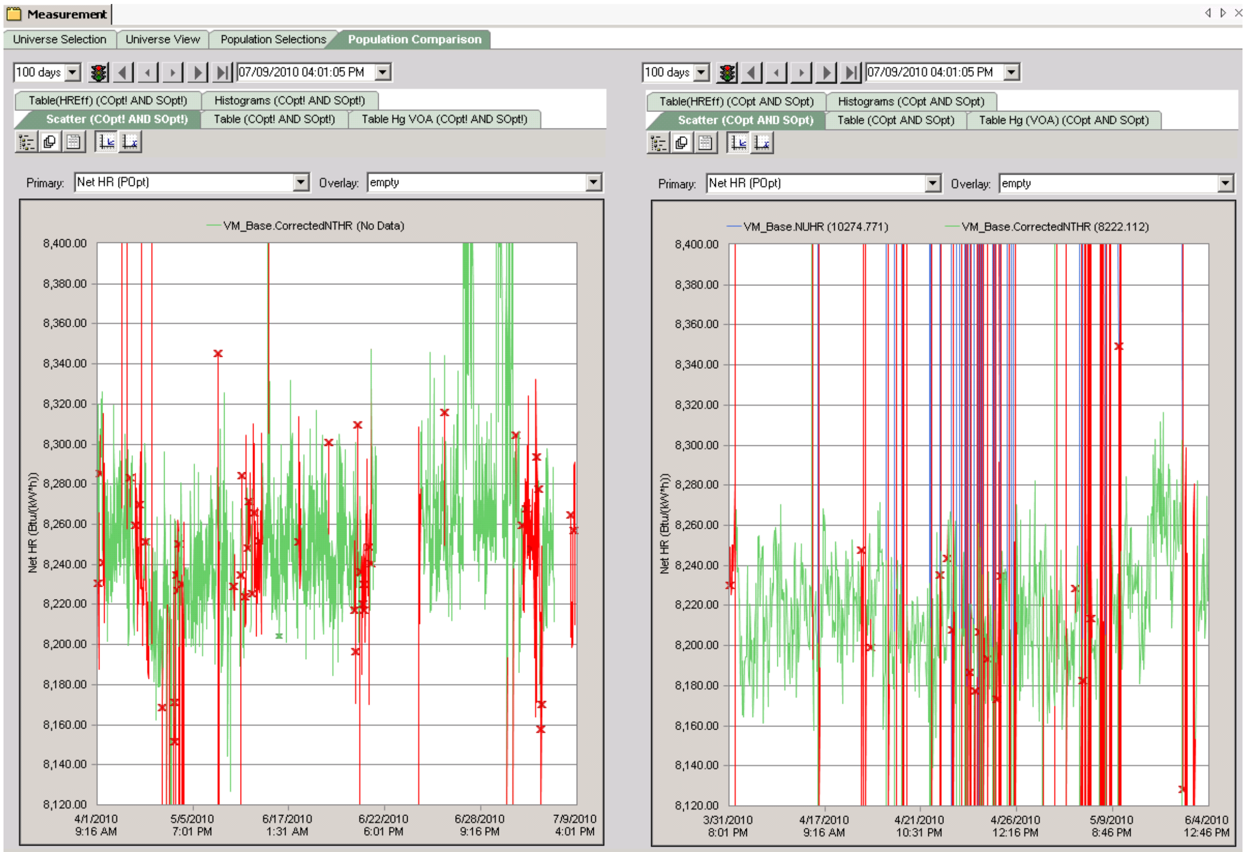

Figure 211: PerformanceOpt Net Turbine Heat Rate (Corrected), MW>880, 3/31/10 - 7/9/10

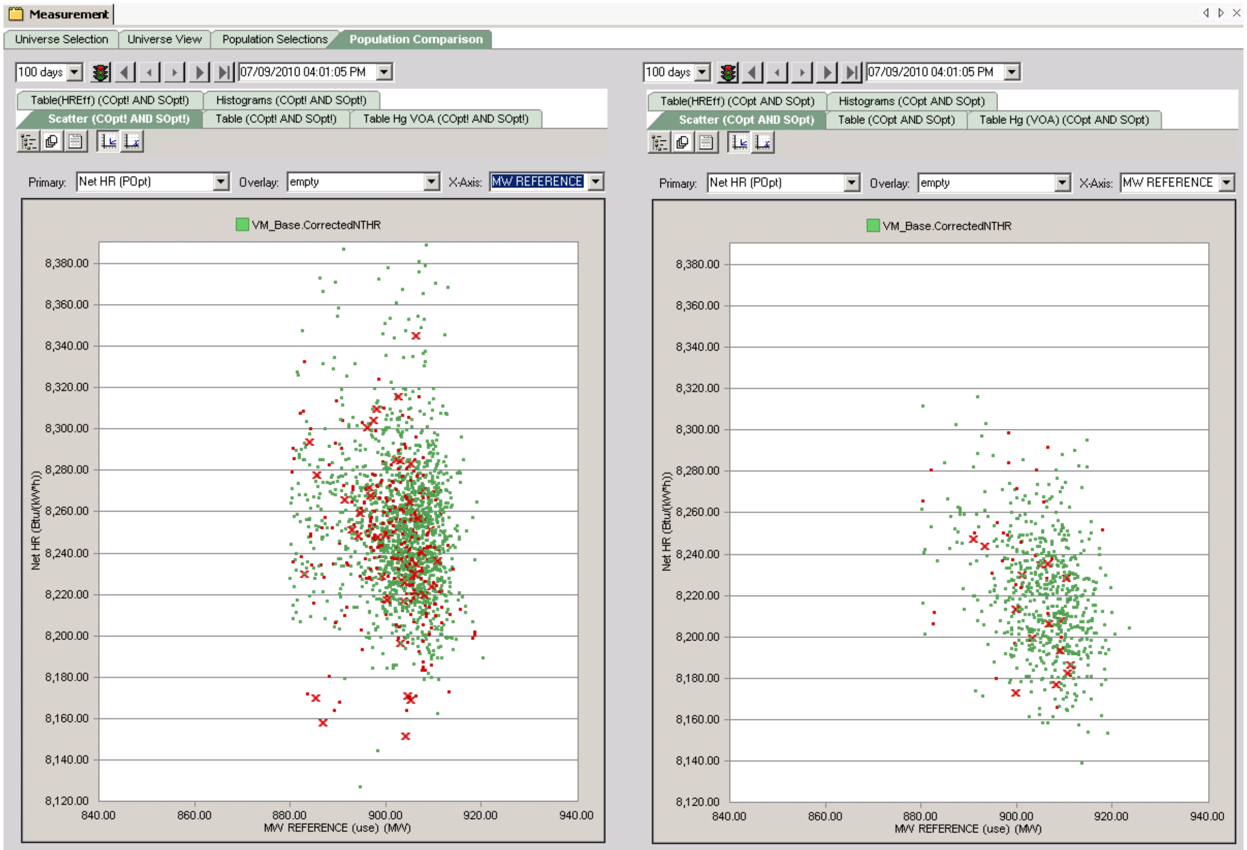

Figure 212: PerformanceOpt Net Turbine Heat Rate (Corrected), MW>880, 3/31/10 - 7/9/10

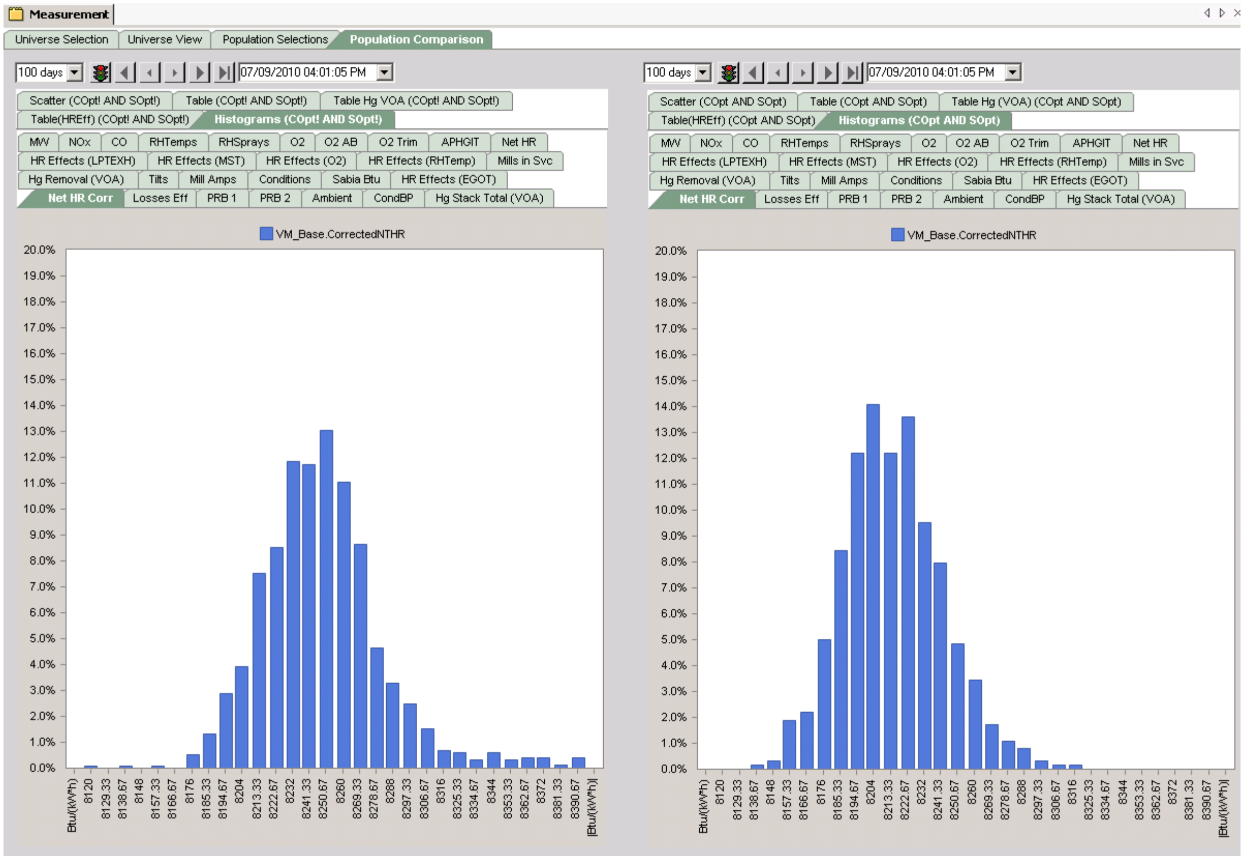

Figure 213: PerformanceOpt Net Turbine Heat Rate (Corrected), MW>880, 3/31/10 - 7/9/10

3.6.6.16 Losses Boiler Efficiency

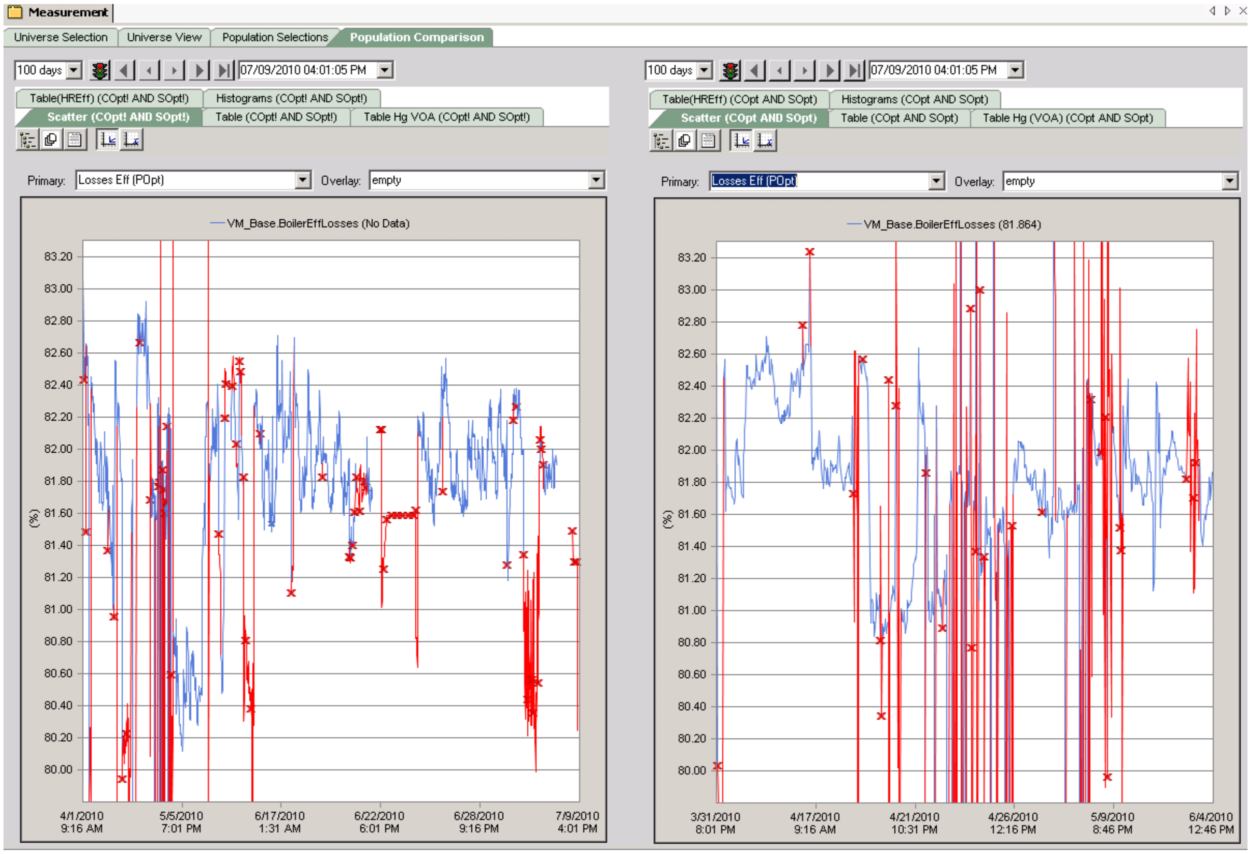

Figure 214: PerformanceOpt Losses Eff, MW>880, 3/31/10 - 7/9/10

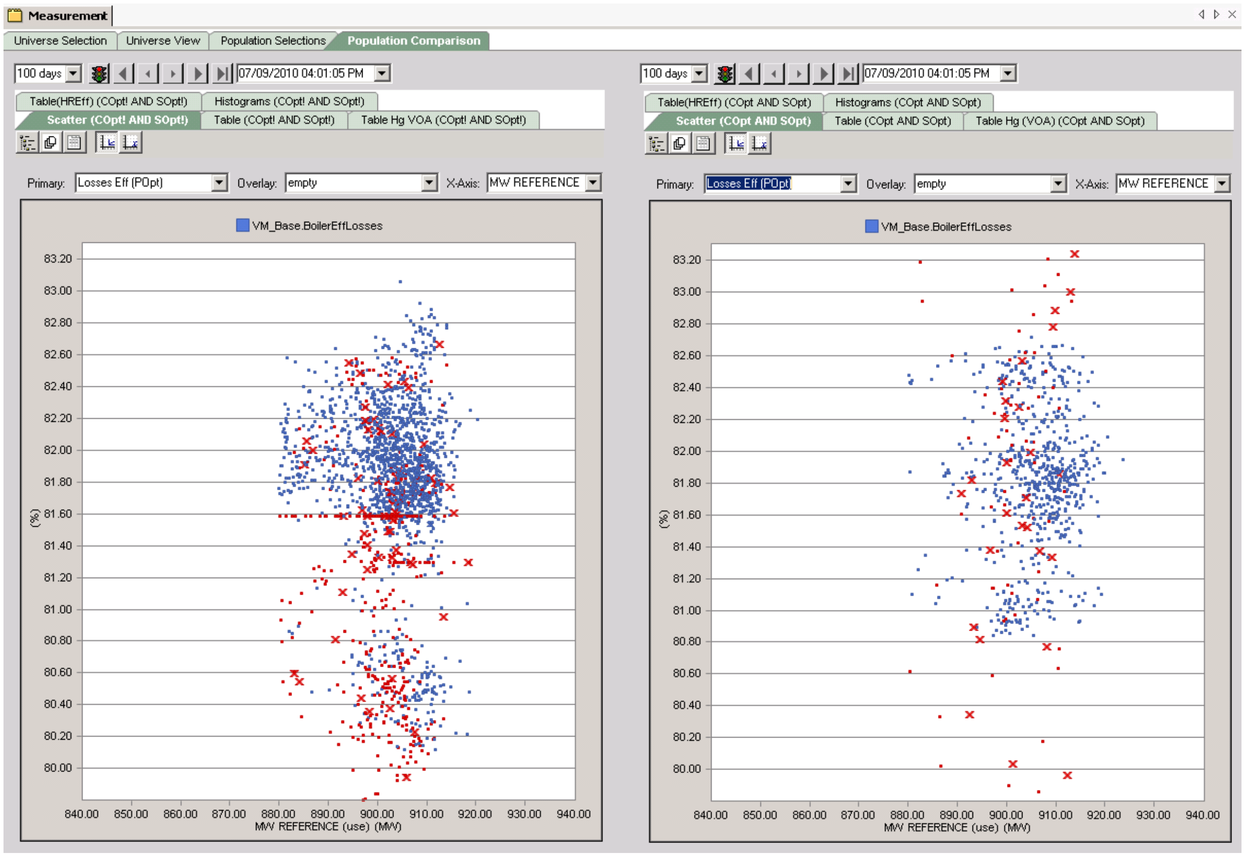

Figure 215: PerformanceOpt Losses Eff, MW>880, 3/31/10 - 7/9/10

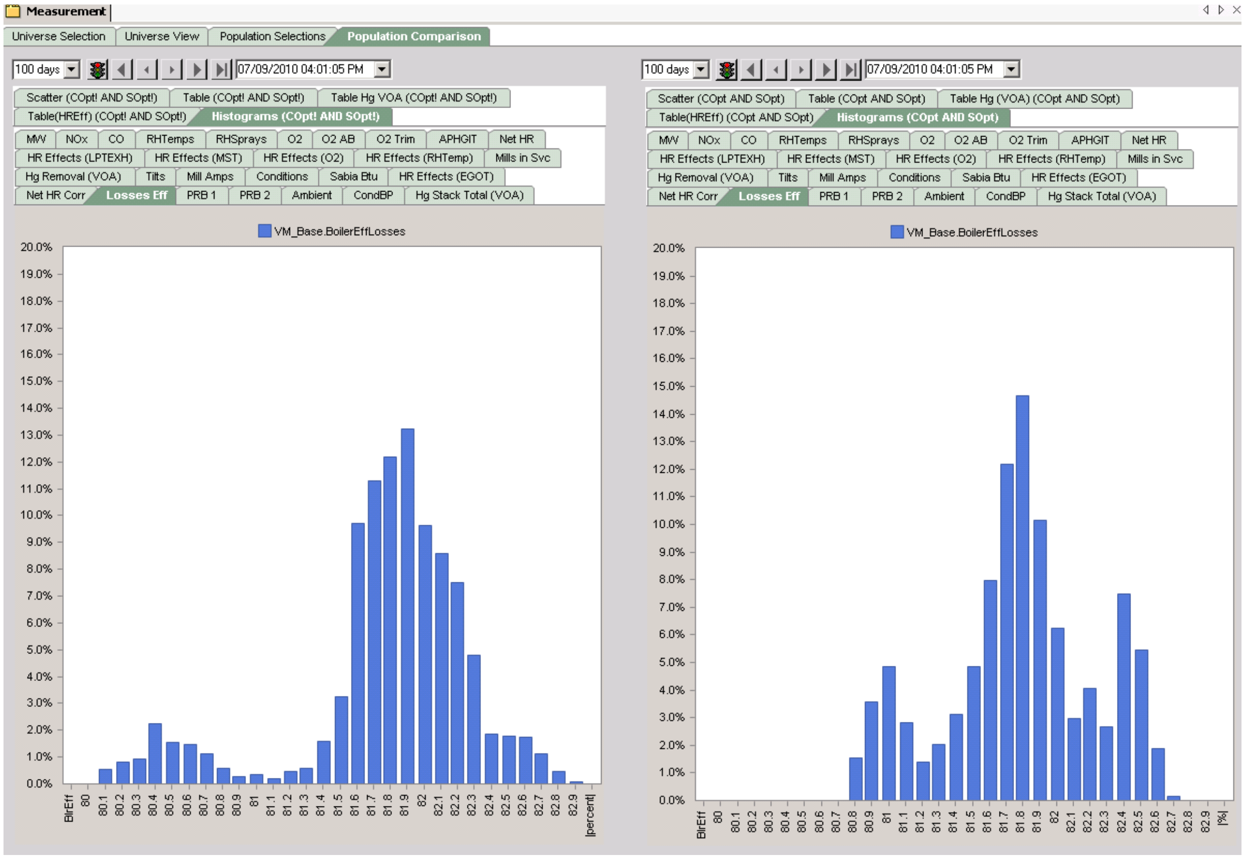

Figure 216: PerformanceOpt Losses Eff, MW>880, 3/31/10 - 7/9/10

3.6.6.17 Modeled Heat Rate

In order to get an estimate of the Heat Rate impact of optimization, despite the fact that Condenser Back Pressure was not held steady during the experiment, the following neural regression models were created. They were then run across the last 100 days of data where MW>880. Because they include Condenser Backpressure as well as other disturbances as inputs, the differences in their predictions should not be based on variability in those, which vary equally in the scenario for both models, but rather in the bias they acquired by training on Optimized vs. Non-Optimized data.

POpt NetHR KPI f(States,Dist)_OFF trained only on data where Optimization was not applied

POpt NetHR KPI f(States,Dist)_ON trained only on data where Optimization was applied

f(States,Dist) = f(MW,Blend,Btu,CondBp,WetBulbTemp)

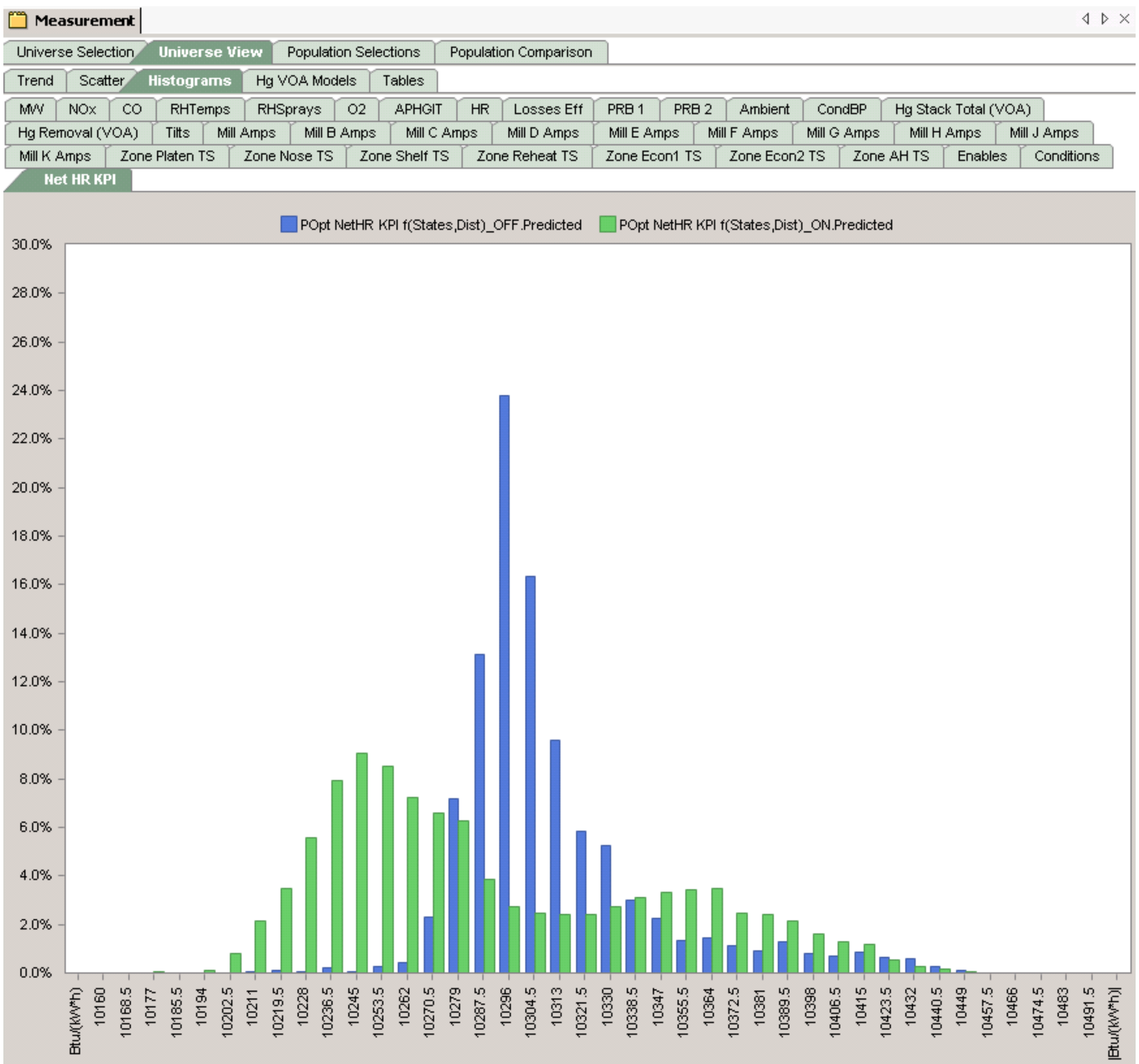

Figure 217: ON and OFF Models of Heat Rate as f(CondBp and other disturbances)

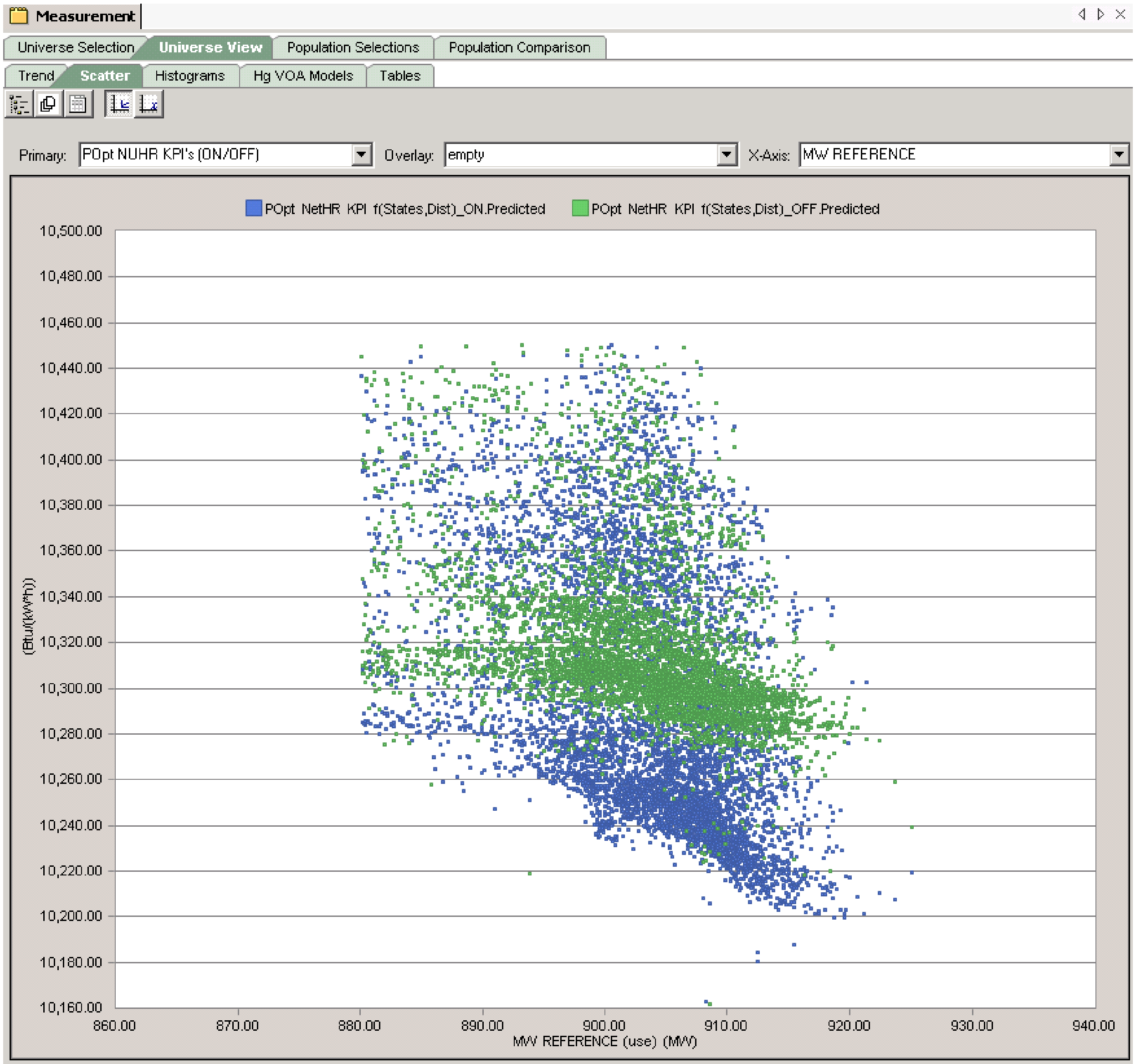

Figure 218: ON and OFF Models of Heat Rate as f(CondBp and other disturbances)

3.6.6.18 Load

Variability in unit load is of course due to varying dispatch requirements. However the method of population selection (a MW range) assures the mean and variability of load in the data analyzed effectively the same in both populations, therefore the load disturbance in the experiment can be expected to be negligible.

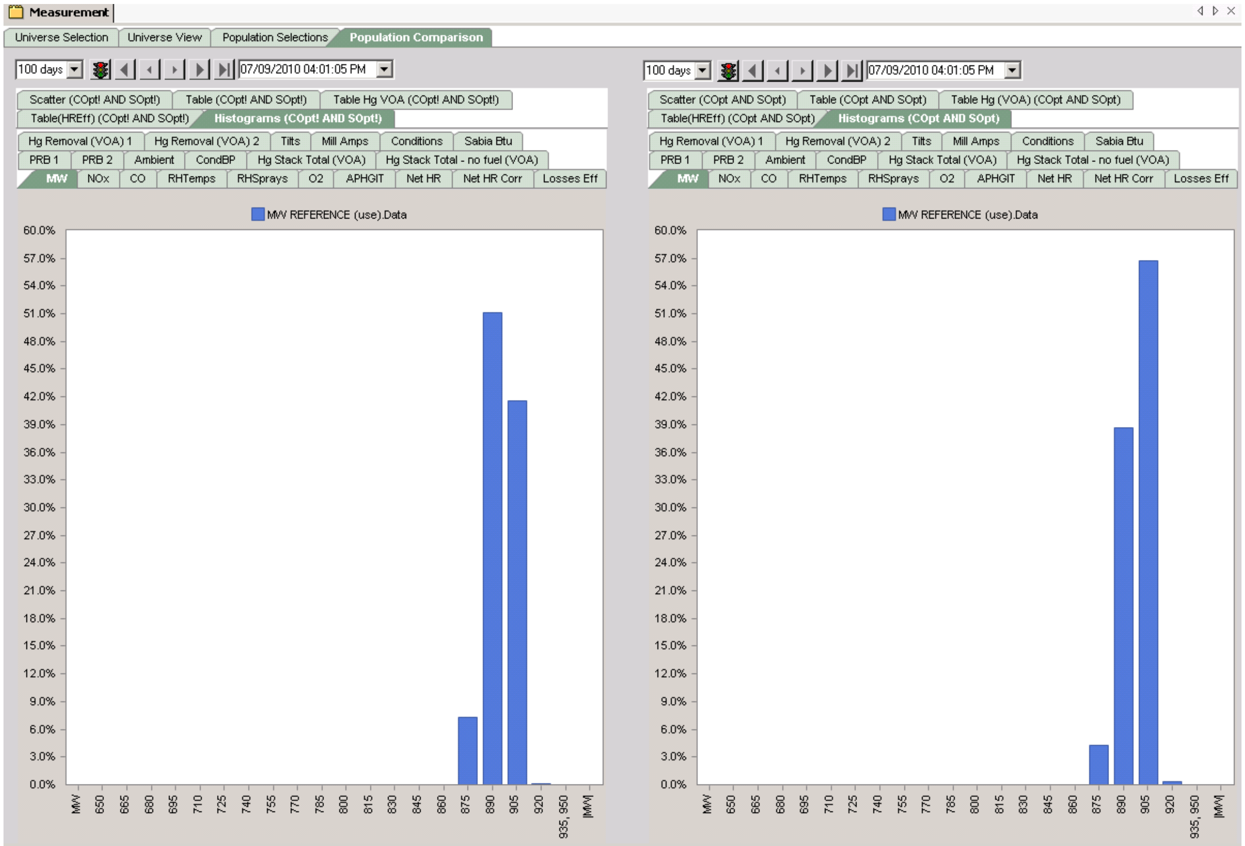

Figure 219: MW Distribution, MW>880, 3/31/10 - 7/9/10

3.6.6.18.1 *Fuel Heating Value*

The data for Fuel Heating Value was taken from the Sabia Coal Analyzer. It should be noted however, that the absolute values do not match expectations due to lack of recent calibration of the analyzer. The lignite fuel used at LMS U2 runs around 6500 Btu/lb, while PRB runs closer to 8200 Btu/lb, and the blend of the period of the analysis (3/31/2010 – 7/9/2010) was around 50/50 (shown in later plots). So all readings are low. The data could still be used however, to compare the populations selected from the time range in question, since drift over that time scale is not significant.

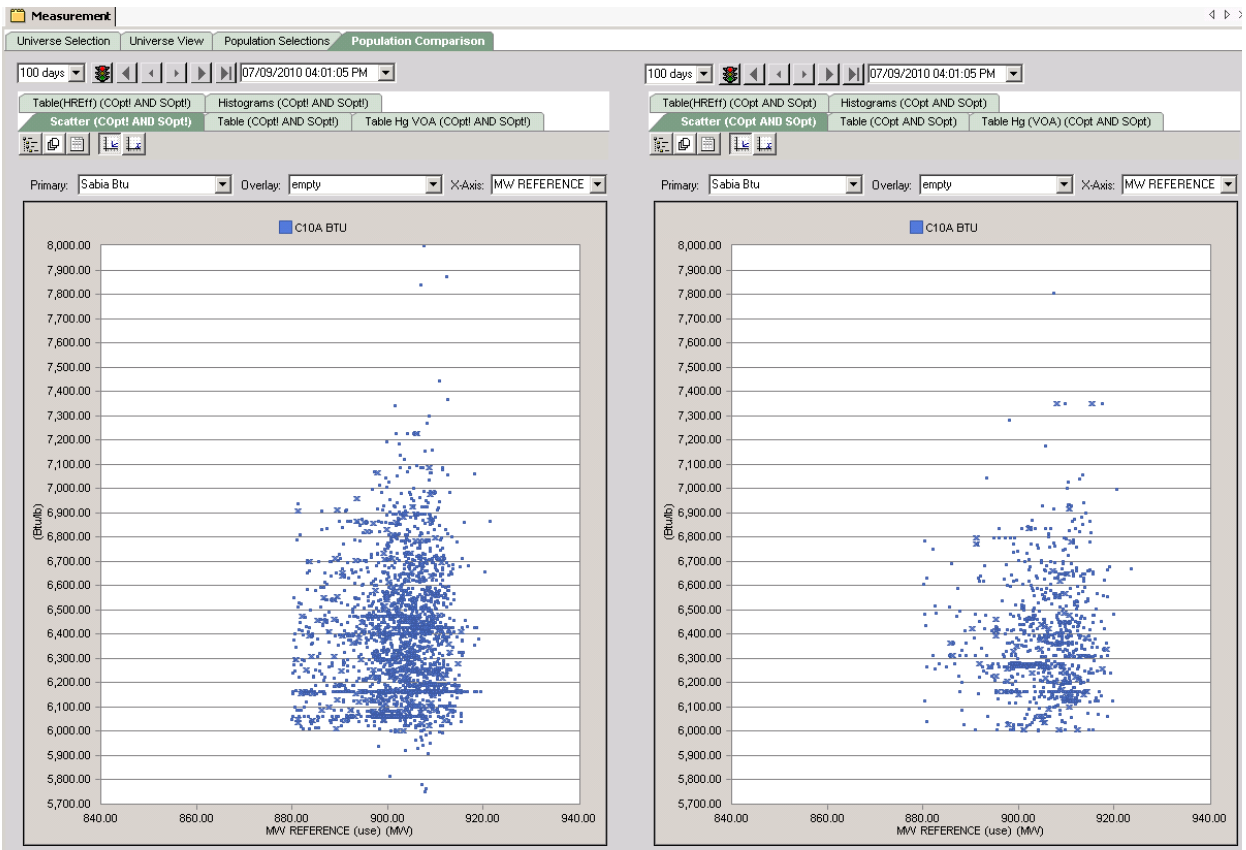

Figure 220: Sabia Fuel Btu Content, MW>880, 3/31/1 - 7/9/10

The desired result of comparison should be that no difference is seen. Fuel heating value has a significant effect on boiler performance across multiple dimensions and if not normalized in both populations, would represent a significant disturbance factor. Over the time range from which the populations were selected, variability in Heating Value is due to more or less random tweaking of the Coal-Fusion blend setpoint by operations, and the natural variability of Btu content in the Lignite and PRB fuels being blended. Regardless of cause, the mean and variability are for current purposes the same in both populations.

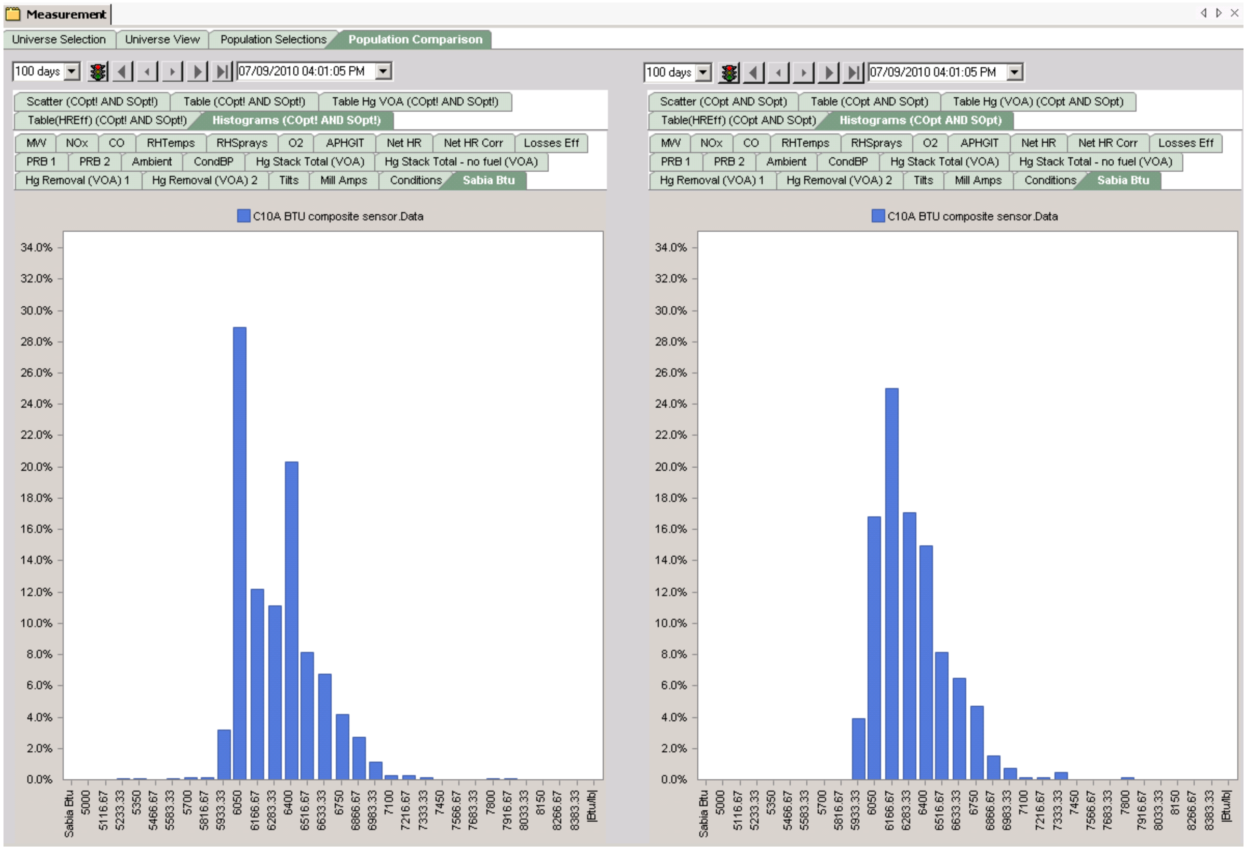

Figure 221: Sabia Fuel Btu Content, MW>880, 3/31/10 - 7/9/10

3.6.6.18.2 PCT PRB Blend

The data for PCT PRB was from the Coal Fusion Fuel Blending System. It represents the setpoint for the blend on the operating belt. The desired result of comparison should be that no difference is seen. PCT PRB blend has a significant effect on boiler performance across multiple dimensions, especially Hg removal/emissions and NOx, and if not normalized in both populations, would represent a significant disturbance factor. Over the time range from which the populations were selected, variability in blend was due to more or less random tweaking of the Coal-Fusion setpoint by operations, and the natural variability of Btu content in the resulting blend. Regardless of cause, the mean and variability are for current purposes the same in both populations.

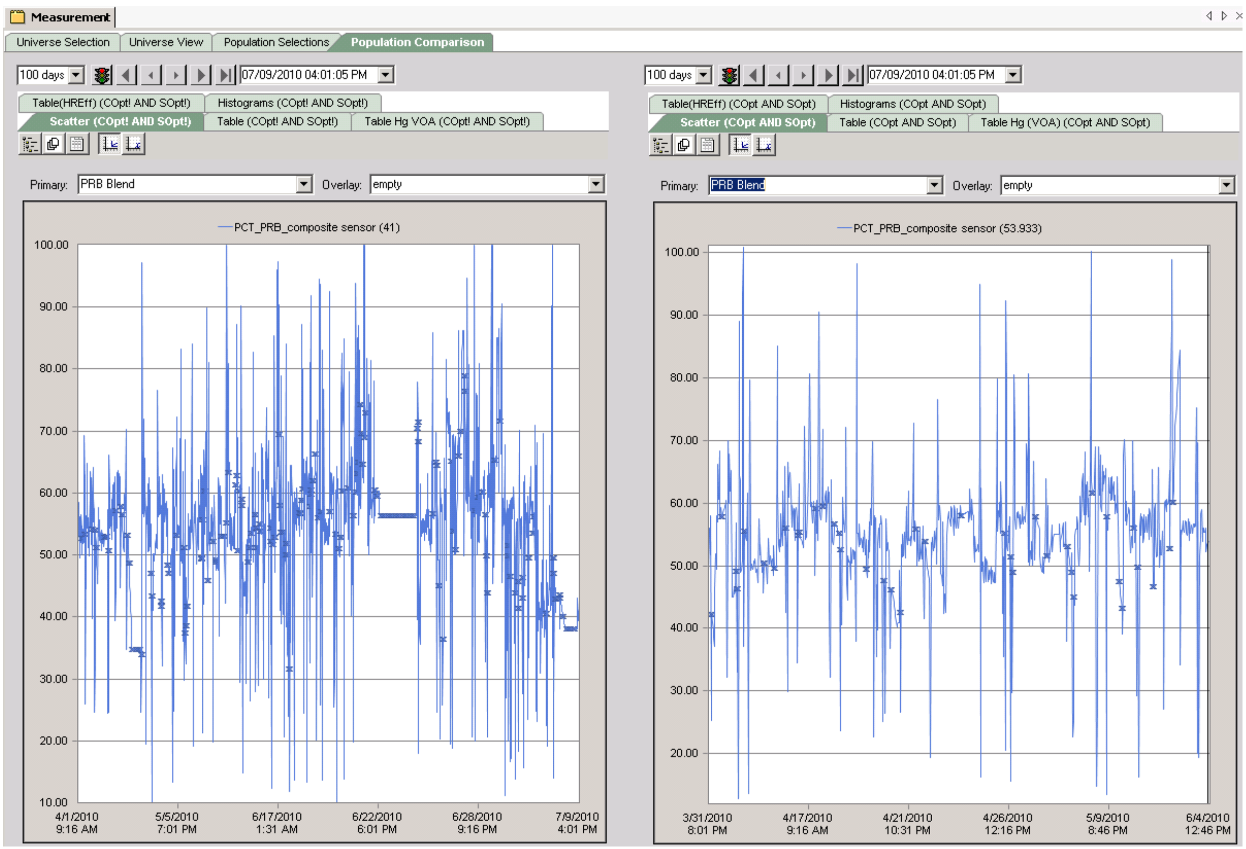

Figure 222: PCT PRB Blend (Coal Fusion Setpoint), MW>880, 3/31/10 - 7/9/10

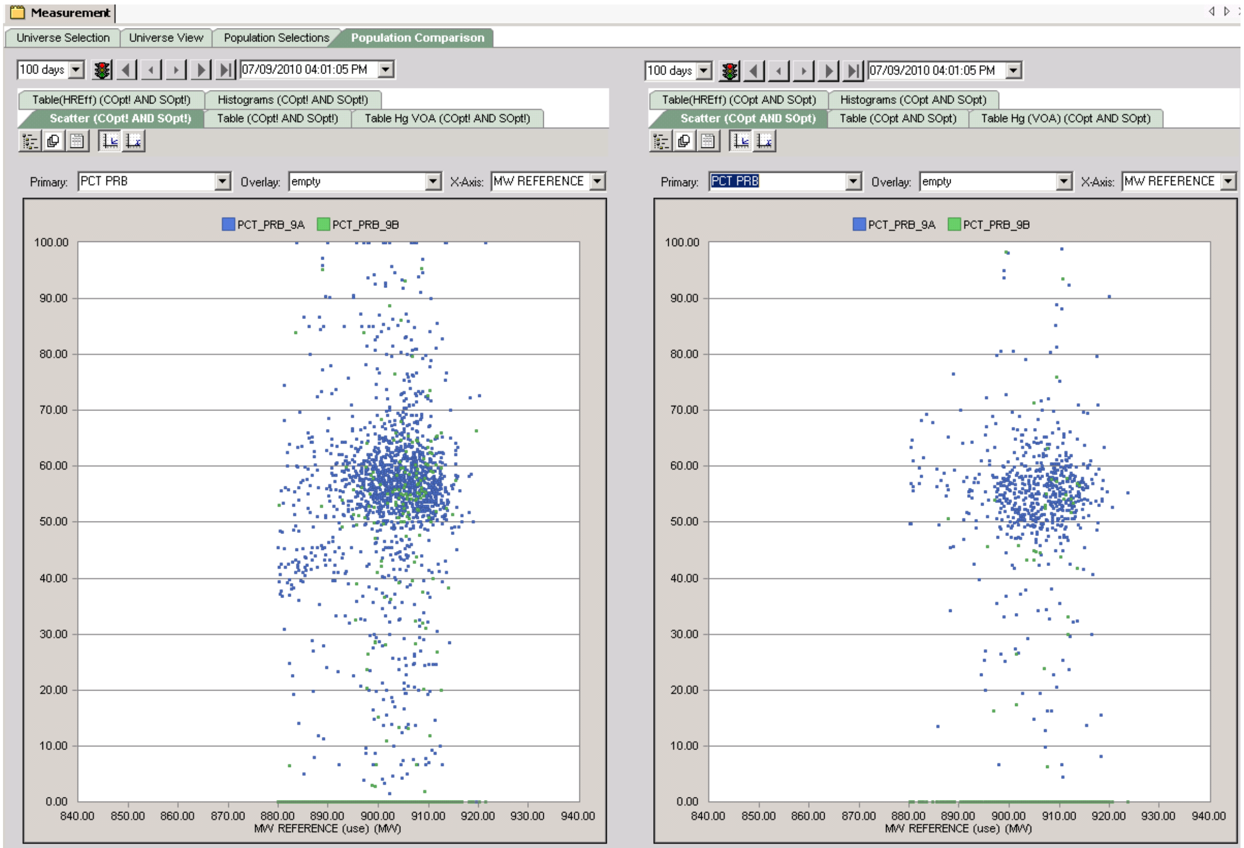

Figure 223: PCT PRB Blend (Coal Fusion Setpoint), MW>880, 3/31/10 - 7/9/10

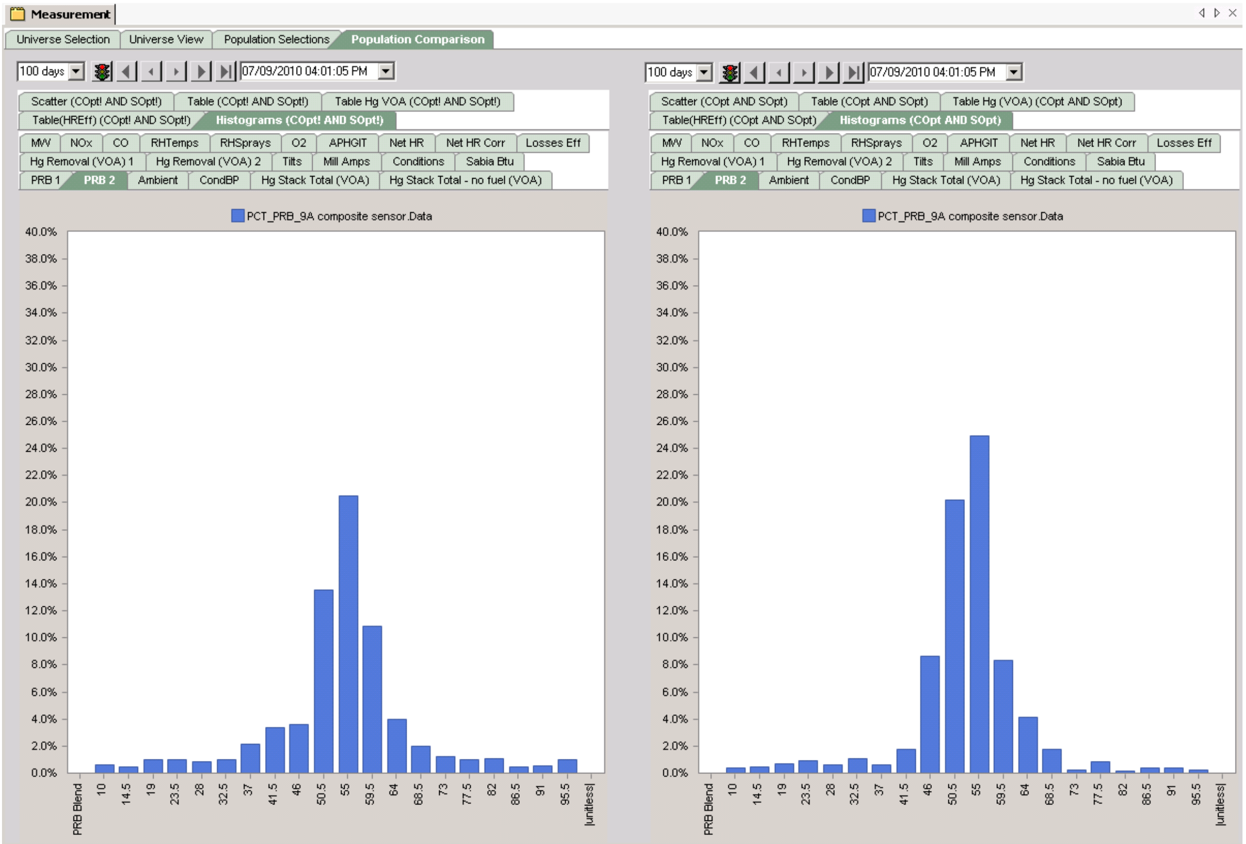

Figure 224: PCT PRB Blend (Coal Fusion Setpoint), MW>880, 3/31/10 - 7/9/10

3.6.6.18.3 Condenser Back Pressure

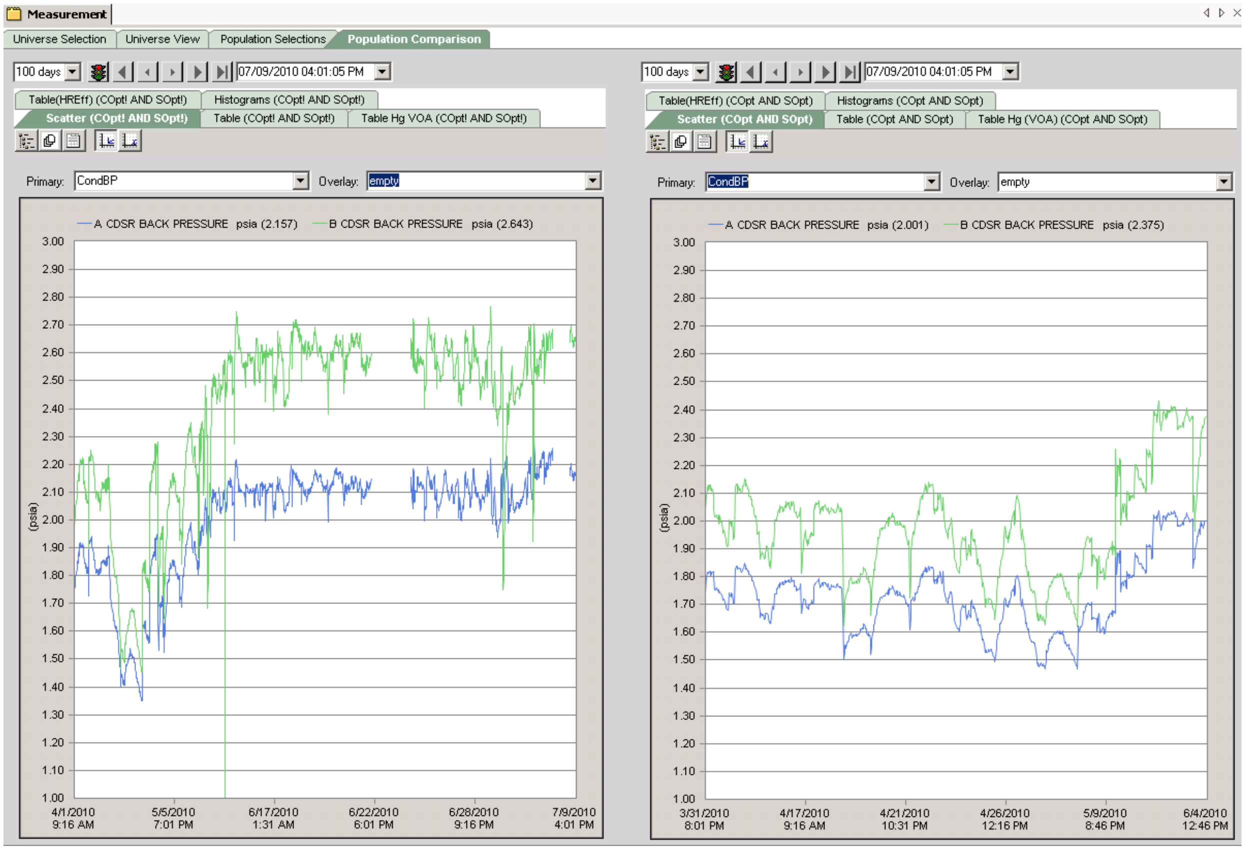

Figure 225: Condenser Backpressure, MW>880, 3/31/10 - 7/9/10

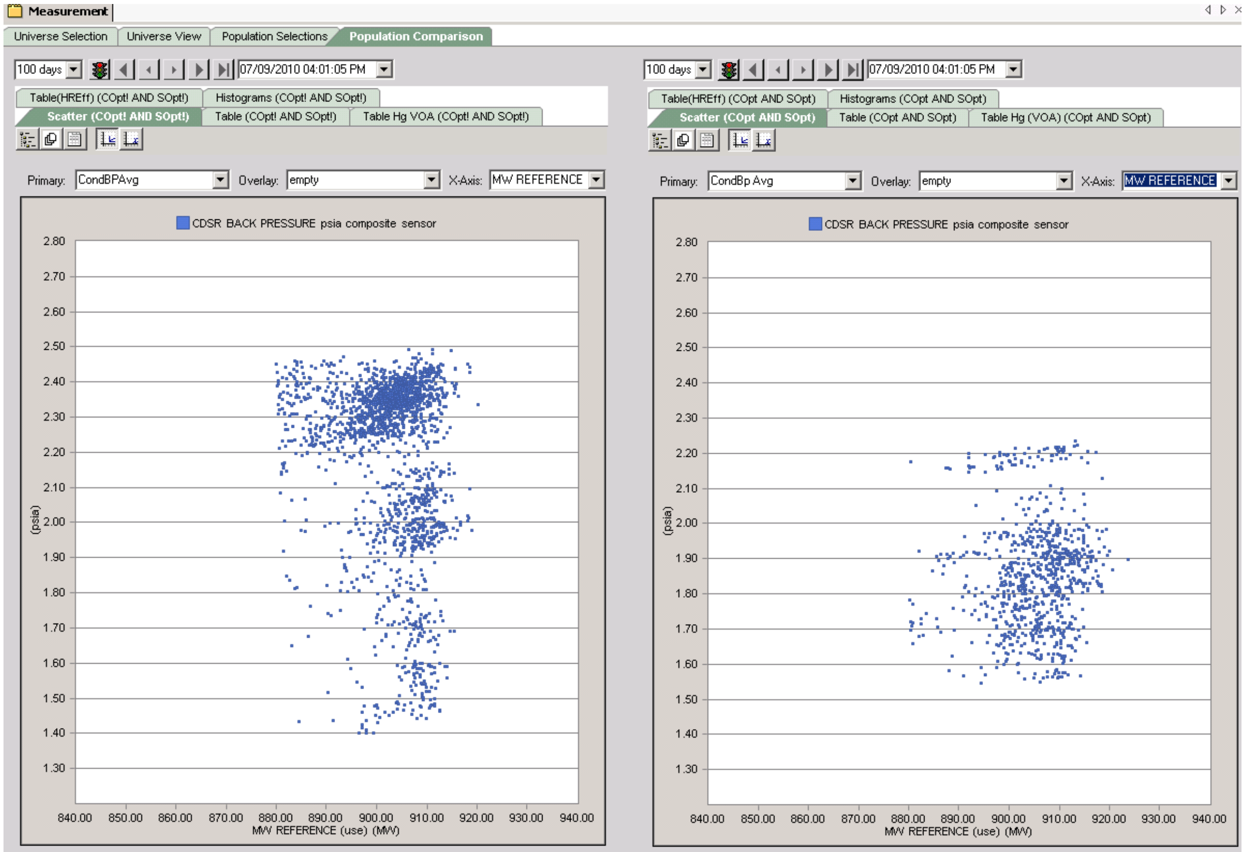

Figure 226: Condenser Backpressure, MW>880, 3/31/10 - 7/9/10

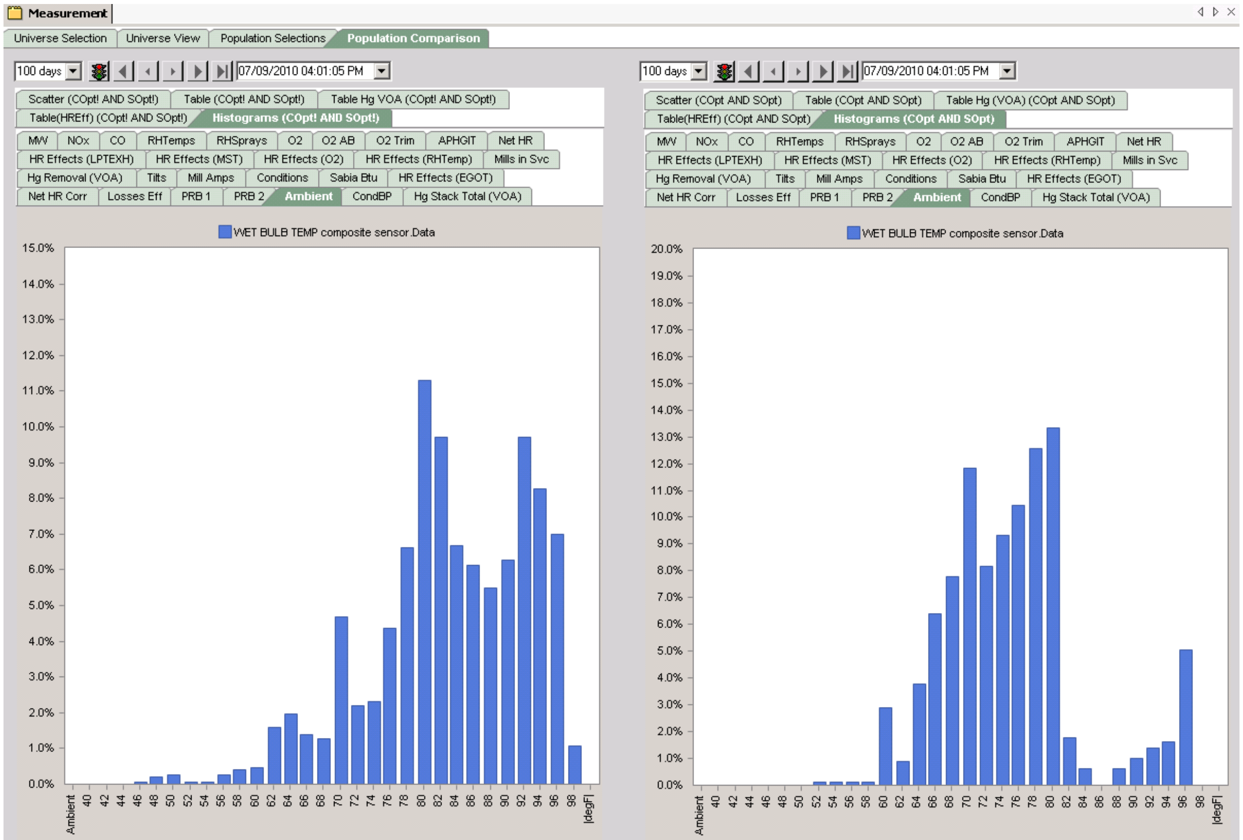

Figure 227: Condenser Backpressure, MW>880, 3/31/10 - 7/9/10

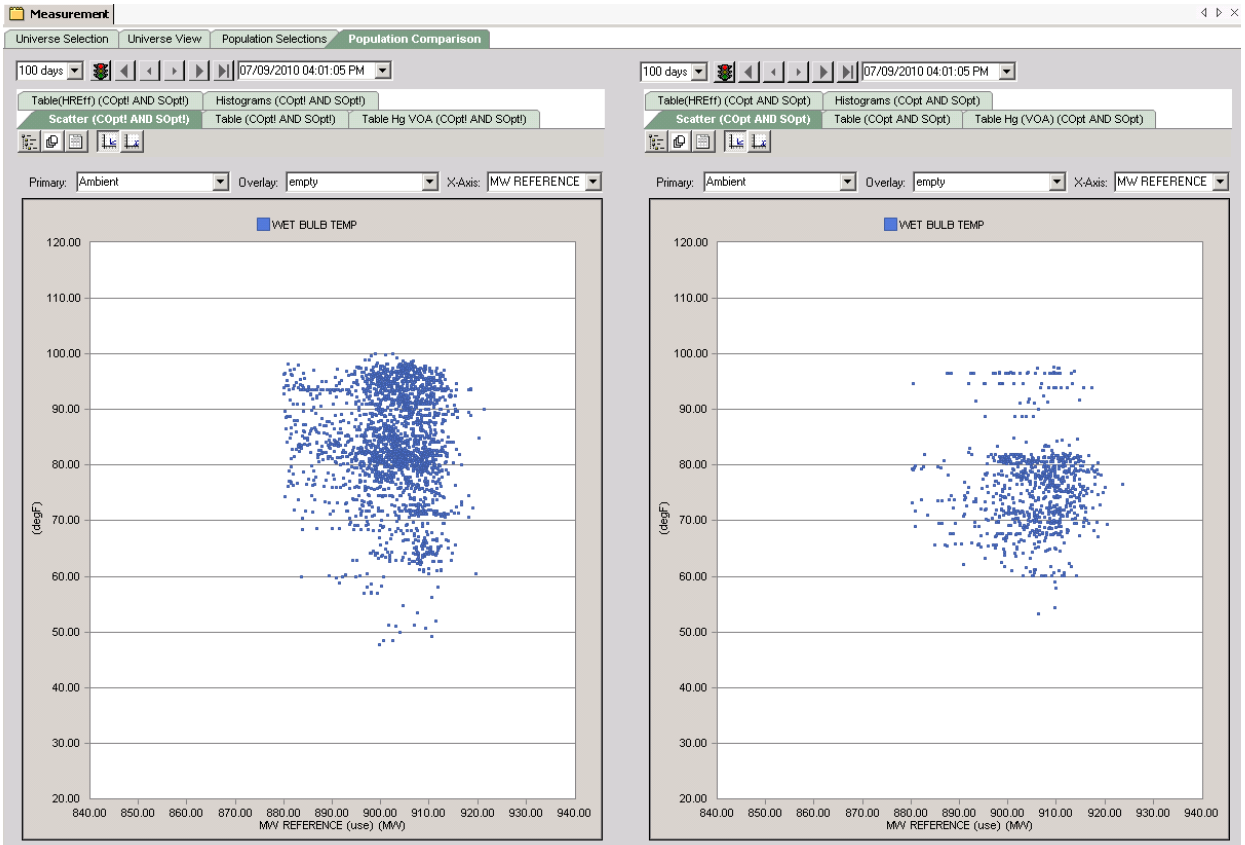

Figure 228: Ambient Conditions

4 List of Acronyms and Abbreviations

(Consolidated list as may be used in this or future reference reports)

API	Application Programming Interface
APHGIT	Air Preheater Gas Inlet Temperatures
BTU	British Thermal Unit
CA	Corporate Agreement
CAMR	Clean Air Mercury Rule
CAIR	Clean Air Interstate Rule
CIA	Carbon-In-Ash
CCPI	Clean Coal Power Initiative
CEMS	Continuous Emissions Monitoring System
CO	Carbon Monoxide
CO2	Carbon Dioxide
DCS	Distributed Control System
DOE	Department of Energy
ERCOT	Energy Reliability Council of Texas
ESP	Electro Static Precipitator
FD	Forced Draft
FEGT	Furnace Exit Gas Temperature
FGD	Flue Gas Draft
FT^3	Cubic Feet
GUI	Graphical User Interface
HMI	Human Machine Interface
HP	High Pressure
HR	Heat Rate
H_2O	Water
ID	Induced Draft
IK	Standard type of long, retractable sootblower
ISB	Intelligent Sootblowing
LAN	Local Area Network
LMS U2	Limestone Power Plant, Unit 2
LOI	Loss on Ignition
Mol Wt	Molecular Weight

mmBTU	Millions of BTUs
mm	Million
MPC	Model Predictive Control
MW	Megawatt
mWh	Megawatt hour
M/year	Million per year
$\mu g/m^3$	Microgram per cubic meter
N	Nitrogen
NERC	North American Electric Reliability Corporation
NH_3	Ammonia
NOx	Nitrogen Oxides
O_2	Oxygen
OEM	Original Equipment Manufacturer
OFA	Over Fire Air
OPC	Object Linking and Embedding for Process Control
PC	Personal Computer
PLC	Programmable Logic Controller
ppm	parts-per-million
PRB	Powder River Basin
PSA	PS Analytical
PTC	Power Test Code
RH	Re heater
S	Sulfur
SA	Secondary Air
SH	Super Heater
SO2	Sulfur Dioxide
SO3	Sulfur Trioxide
TC	Thermocouple
TDL	Tunable Diode Laser
VOA	Virtual On-Line Analyzer
VPN	Virtual Private Network
V&V	Verification and Validation