ASA 1999 Quality and Productivity Research Conference

May 19-21 1999, Schenectady, New York

Session: Useful New Six Sigma Tools and Challenges

IMPROVEMENTS THROUGH PROCESS ADJUSTMENTS

Carlos W. Moreno, Chairman & Founder, Ultramax Corporation

513-469-8629, carlos.moreno@ultramax.com

Abstract:

One way to decrease variation in key production processes is by improved adjustments of their control inputs. "Dynamic Optimization" does this and more:

- It can be applied by an engineer/black-belt "by hand"; and can be integrated with DCS/SCADA systems for on-line automatic performance optimization even as conditions and objectives change.
- It can simultaneously address multiple (measurable) objectives, such as several measures of variation, yields, production rates, product characteristics to be maximized/minimized such as strength and impurities, consumption, losses, safety, emissions.
- It uses sequential modeling and optimization. Given a set of objectives, adjustment of control inputs such as temperatures, pressures, flows, depth of cut, cycle times, etc. are optimized in usually 30-80 readjustments without requiring prior data or prior models. A run with each adjustment is usually 0.25 to 2 hours for continuous processes, or the normal batch time.

Typically in the last ten years, the bottom-line gains have been several $100K/year per application, a payback of a few months.

Using this tool can increase the profitability impact of Six Sigma programs.

Introduction

Production process performance, including consistency, yield, production rate, product characteristics, costs, and other ancillary results, depend a lot on how the control inputs to the process are set or adjusted.

Historically it has been proven that major improvements are available in many production processes by implementing better adjustments.

This paper presents aspects of one technology to achieve better process adjustments, technically described as "*Sequential Empirical Optimization*", and known as "*Dynamic Optimization*" in certain application areas. One version of this technology is a tool marketed under the name of ULTRAMAX®.

Scope of Dynamic Optimization

These are the predominant patterns of thought and consequent technology that drive the ULTRAMAX solution to implement "Dynamic Optimization" (DO).

A. Applicability

The main purpose of Dynamic Optimization is to improve the profitability contribution of a production process. The pivotal focus is to achieve this through better adjustments or settings of the control inputs for a process that has already attained a state of reasonable statistical control.

Profitability or other objectives can be defined with any quantifiable aspect of process performance that is relevant to the user. This includes process/product ‘variability’ as used in Six-sigma applications. When costs/revenues are considered directly, one of the outcomes is the implicit assignment of economic equivalents to variability measures. Goals are represented by an objective function to be maximized or minimized, subject to constraints on inputs and outputs to take into account other considerations such as capacities, safety, technical and legal restrictions, etc.

D.O. is one of the improvements enabled by a process being in sufficient control, as would happen from the application of the Six Sigma method. In a synergistic relationship, D.O. can in turn help better achieve the Six Sigma objective of reduced variability, together with reduced costs and increased productivity.

This tool (D.O.) will also help identify when problems arise, but this is not its main purpose. To solve problems generated by special causes we revert to well established Quality Control technology within the Six Sigma method.

The two first steps in applying D.O. are:

1. Define objectives, how performance is measured; and select the control[1] and uncontrolled[2] inputs that are most likely to affect performance.

2. Test that the process is in “sufficient control”, that is, the results are reasonably reproducible. This is a simplified process capability study.

Note in particular that each measure of process capability (e.g., a CP) does not have a single value for a process -- it depends on how the process control inputs are adjusted. Thus, the latent or best process capability can be determined only after optimizing the adjustments.

Note further that optimal adjustments depend on:

- uncontrolled inputs: physical conditions such as raw material characteristics and environmental conditions;

- economic conditions such as materials/energy costs and availability, whether in a sales or capacity constrained production;

- objectives, such as specifications

that are not necessarily static.

By comparison, solutions using DOE/RSM, Neural Networks and models based on first principles are too static (and too costly). EVOP and Simplex are more dynamic, but not as effective because of their rudimentary technology[3].

---

1 Inputs that can be adjusted or set, frequently the targets (setpoints) for first-level control devices.

2 Inputs such as the characteristics of a batch of raw materials, or environmental conditions such as humidity.

3 This is stated with considerable respect and recognizing that such simple technologies yield so much results. D.O.’s significant increases in reliability and performance have been obtained by developing and applying proportionally much more technology – but which is virtually transparent to the user.

B. Sequential Learning and Optimization

A process produces product and data. This data can be used for accounting purposes and to detect special causes, and also to characterize the process so as to learn how to get more bottom-line value from it.

The fastest learning is when available data is used immediately. Since production data is generated sequentially, to take full advantage of the data one needs sequential statistical methods. Sequential modeling and optimization – each time new data becomes available -- not only advances getting improvements because data is used sooner, but the advanced awareness also leads toward avoiding risks and accelerating getting the right data – that is, earlier/higher process performance.

Some of the technical characteristics of ULTRAMAX's D.O. are:

- Models (Y=f(X) where Y are the outputs and X the inputs[4], some being adjusted and some uncontrolled) are based on Bayesian statistics to work better in an environment of insufficient data (which is useful to start improving right away) and to avoid overreaction to noisy data.
- Models are locally accurate so as to focus the ability to predict accurately only in the area of interest, i.e., around the perceived best running conditions. This also reduces the distortion[5] and the extra numerical efforts in modeling the process outside the areas of interest.
- Models are quadratic polynomials[6] (subsets with insufficient data), which are quite effective given the above approach.
- It recognizes the local region (of combination of inputs) for which the prediction models are sufficiently accurate: the Area of Confidence (AOC). Advice for adjustments for the next production run is given within the AOC to be reasonably assured of the results to be obtained with the production process[7]. The AOC moves towards the optimum as models are updated with new sequential data that moves towards the optimum, this creating a self-supporting synergistic effect.
- The mechanism to provide a sequential Advice for the next adjustment of the production process minds maximizing/minimizing the objective function while satisfying input and output constraints, the AOC as mentioned above, controlling making abrupt changes, and maintaining the robustness of future models to be created with the new data generated.

By 'optimum' in D.O. we do not mean the optimum in the region where the process has been operated in the past[8] upon which prediction models are created, but wherever it could be

[4] Note that here X are the process inputs, not internal process variables that explain or cause the final outputs. The frame of reference is that of a Decision Input/Output Diagram, not an Engineering Input/Output Diagram. In this approach, intermediate variables, that are a consequence of the inputs, are also dependent, results or "output" variables.

[5] Making the realistic assumption that the correct model structure (equation) is not available.

[6] Taylor expansion of second order.

[7] The tradeoff between certainty in future results – little extrapolation -- and the speed of getting to the optimum – more extrapolation -- can be controlled by the user, but users frequently rely on the default settings in the technology.

[8] Whether during regular production and/or variations generated by DOE or any perturbations implemented to generate data necessary for certain Neural Networks.

operated[9]. Sequential modeling/optimization methods enable D.O. to learn about process behavior as the adjustments move towards the optimum where there is no historical information.

To implement the above technology the third stage in D.O. is:

2. Engage in these steps of sequential cycles, all of which can happen automatically in a closed-loop installation integrated with DCS/SCADA[10] systems, can happen stand-alone manually, or some mix of the two.
   - Adjust (set) the control inputs[11].
   - Run the process until the output measurements are representative of the values of the inputs, typically ¼ hr. to 2 hrs (or the length of the batch process).
   - Collect the input and corresponding output data for the new run, and when applicable, the values of the uncontrolled inputs[12] for the next run(s).
   - Enter the data into the computer program.
   - Generate a new Advice. The technology updates the models with the new data (called Learning) and uses the new models to generate the new Advice (called Synthesis).
   - Especially in the first series of advices the operator or engineer decides that an advice is satisfactory, or if deemed necessary can modify it based on personal knowledge and experience. Then he/she goes back to repeat the first step of the sequential cycles.

This flow of information is illustrated in Fig. 1, and the kind of results to be obtained is illustrated in Fig. 2. This procedure yields the highest payoffs when applied to repetitive operations – let us say, spending more than 200 hours/year producing a product.

After a significant data base has been collected, through Engineering Analysis, it is possible to identify the vital inputs which are most relevant, and whether other important inputs or factors need to be identified to explain results. After the optimum is achieved, Engineering Analysis tools help understand bottlenecks to further improvements, which would lead to certain cost-effective modifications to the process itself.

The section below "Results from two applications" describes applications in more detail.

---

9 … as a continual improvement from where the optimization got started; i.e. climbing the "mountain" of performance on which the process is being run initially. D.O., used mostly in production, does not attempt to perform global optimization if it happens to lie on the other side of a valley of lower performance. Identifying a better mountain is better done in an R&D environment, using first-principles and/or specialized DOE. Once a better "mountain" is identified, then D.O. is the technology to refine the new local optimum and maintain it.

10 Distributed Control Systems; Supervisory Control And Data Acquisition.

11 Control inputs remain absolutely constant until changed by the operator. One example is the target value (not the actual) for a control device, more generally, the position of a knob.

12 Uncontrolled inputs are (basically) not affected by the control (adjusted) inputs.

Sequential Empirical Optimization (SEO) Cycles

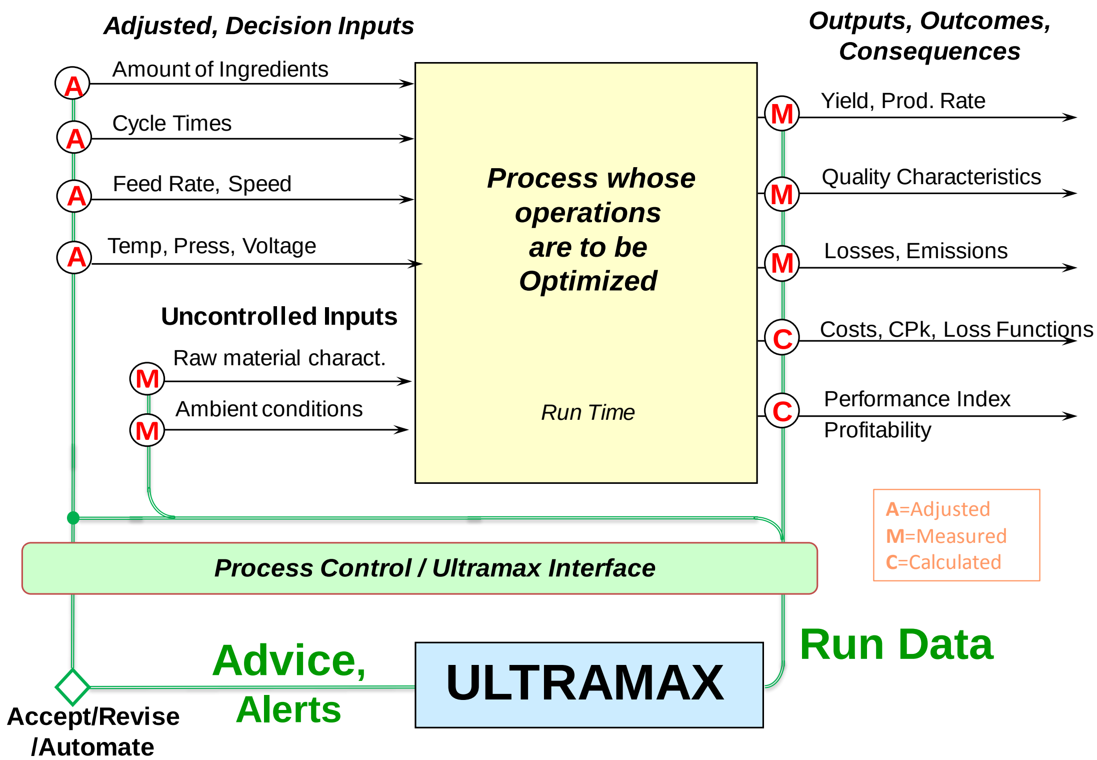


Figure 1: The Decision Input/Output Diagram.
The specific variables are defined by the users for each application

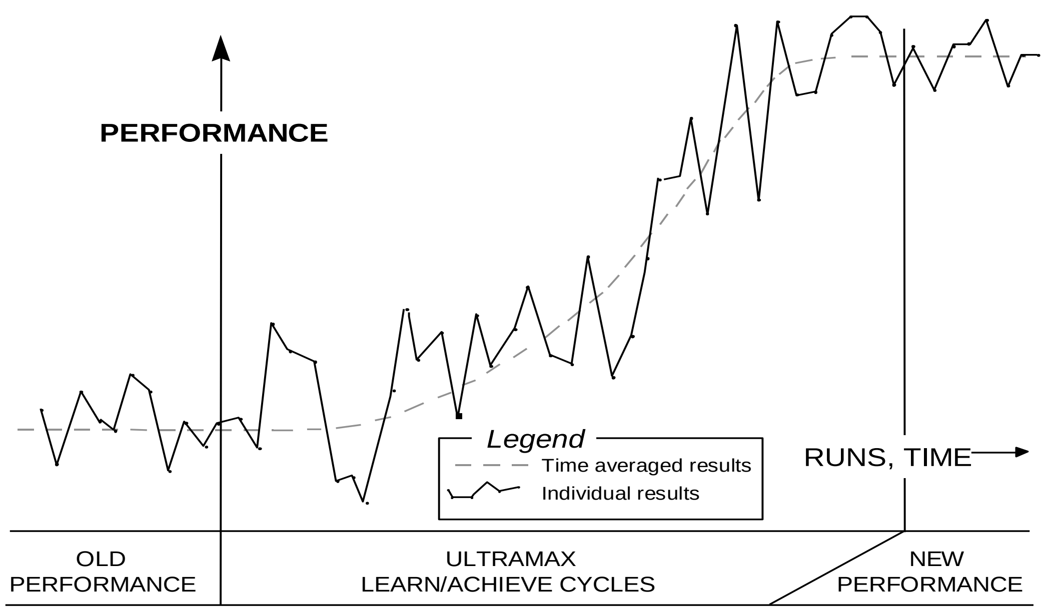


Figure 2: A pattern of improvements obtained through sequential adjustments.
The first 10 runs were made at constant inputs set at the baseline.

3. How and why D.O. has advantages

The metrics for the performance of Adjustment Optimization technologies are based, of course, on the improvements to the performance of the process being optimized. In addition one may include other costs incurred and benefits obtained.

From a business point of view, the most inclusive metric of the performance of an Adjustment Optimization technology is the cumulative process performance since the inception of applying the technology, including any data gathering stage. This metric reflects that a superior technology needs to increase process performance ***quickly***, and in the long run keep it ***close*** to the optimum. Recall that, as suggested above, the optimum is not necessarily a constant, but it depends on conditions and objectives, which may change significantly with time. ULTRAMAX's D.O. was designed to maximize this metric.

To compare various adjustment optimization technologies as applied to a target process, we would have them all start in the same region of process adjustments, and then track the cumulative performance, ideally without human intervention, for as long as desired. This can be done in a scientifically reproducible way when the target process is computer-simulated, including the changes in the values of uncontrolled inputs and other random effects.

Factors related the superiority of D.O.:

- Because D.O. is based on sequential modeling and optimization it can approach the optimum (or optima, depending on conditions) with much less data (fewer runs) than DOEs or EVOP, and of course, it can maintain it as conditions change. For the same reason it can do much better than Neural Networks, especially when the historical data used for training the NN was obtained away from the optimum (as it is usually the case). It is more reliable than SIMPLEX because it is model-based, makes more use of past data, and can address explicitly uncontrolled inputs.
- It is much less costly than alternate methods that would require taking the process out of production to generate data, with the consequent consumption of labor and materials and losses in sales.
- It is simpler because it requires much less statistical knowledge. In some respects, it requires none, as it is evident when running in a closed-looped mode. However people will continue to need statistical, engineering and business knowledge -- such as what black-belts and engineers have – for when D.O. detects "alert" conditions that require analysis to evaluate and resolve.
- The Game Plan (Optimization Focus) can be improved by the black belts, engineers and managers as new awareness about requirements and/or about the process is acquired while doing optimization.

Results from two applications

1. Vane Grinding Operation

Business Situation

GE Aircraft Engines (GEAE) in Cincinnati, OH, in 1989, was faced with a capacity-constrained production situation for a particular high-volume aircraft engine.

A key constraint to production was the availability of a turbine vane.

The Process

A potential bottleneck process was identified as the grinding of the original cast to generate the forward inner and outer bands. This process was deemed critical because it is the reference surface for future machining, which produced over 20% rejects.

The process was creep-feed grinding, which removes large amounts of stock in one pass and leaves a high quality surface.

Objectives/Outputs

The translation of the general business objectives into specific measurable objectives/outputs were:

1. *Achieve minimal deviations from targets for measures at four locations and calculated taper and flatness*[13]. The relevant data was the average and standard deviation of 24 vanes ground with the same setting of the control inputs, the raw data obtained with an automatic digital measurement device.
2. *Increase the gross production rate*. Production rate was affected by the fact that creep-feed grinding wheels were consumed in about two hours of operation, and it took some 50 minutes to replace and set them. Gross production rate was calculated measuring the instantaneous production rate, the consumption rate of the grinding wheel, and taking into account the wheel changeover time.
3. All this data was supplied to ULTRAMAX, which through certain parameters provided by the users, was translated to “performance loss functions” to be minimized while the process ran within constraints.

Other outcomes from running the process were considered relatively unimportant, including the possible increase in the grinding wheel usage cost.

Inputs

The engineers and operators selected, based on their own knowledge and experience, the following inputs (from the 40 or so in the control panel):

- Four control (decision) inputs that were most likely to provide improvements if adjusted better: Dress rate, Feed rate, Feed Length, Wheel speed.
- One uncontrolled input that might explain other variations in results: Wheel radius.

All other adjustable control inputs were kept constant at their best known values, and other uncontrolled inputs, such as wheel hardness, were ignored for the time being.

[13] Note the not-so-subtle difference from the traditional criterion that a part was “good” if it was within specifications, thus ignoring that when within specifications there can be significant different levels of quality with their consequent effects on profits. The new objectives were in spirit similar to maximizing CPK, except that there were seven CPKs to maximize. The balancing among the seven variabilities was done by using Ultramax’s “Performance Loss Functions”.

Results from Dynamic Optimization

Plots of the most important variables from 27 sequential readjustment cycles are presented in Fig. 3. Each adjustment was run for about 45 minutes to grind 24 vanes – namely, about 20 hours of optimization work spanning two weeks.[14] The net results were:

- Variation from target was reduced by 33%, resulting eventually in a 75% reduction of scrap due to future machining.
- Production rate was increased 7% -- concurrently and in addition to the throughput increases due to scrap reduction.

These results were obtained largely by these re-adjustments:

- reducing the dressing rate of the grinding wheel – and thus almost doubling the life of each grinding wheel,
- maintaining and improving quality (and reducing instantaneous production rate) by reducing the feed rate.

Bottom Line

In two weeks removed a bottleneck to deliver engines.

The scrap reduction saved about $250 K/year.

The process was always capable of these results; all that was needed was a means to adjust the process better.

[14] For more details see Bhateja and Moreno (1989)

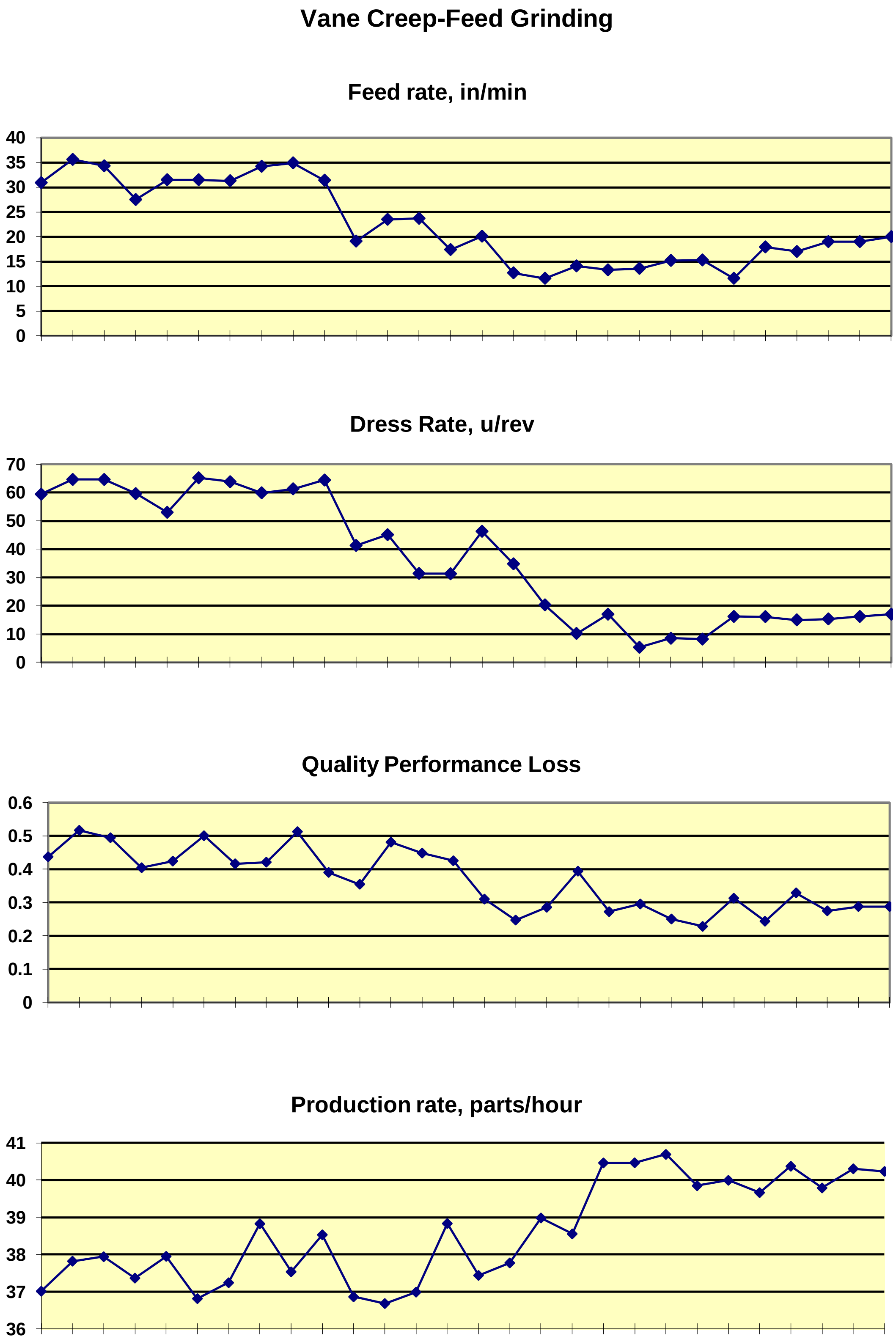


Fig. 3: Sequential data in the optimization of Vane creep-feed grinding

2. Combustion Optimization of an Electric Power Generating Boiler

Business Situation

The Illinois Power Co. in 1996 was faced with two challenges:

1. Bringing their operations into compliance with the 1990 Clean Air Act Amendment at the lowest possible capital investment.
2. Be a least-cost provider of electricity in order to meet the challenges of a developing competitive market.

The Process

This situation applied to the 235 MW Hennepin Power Station's Unit 2, with a Coal Tangentially Fired Boiler from Combustion Engineering (ABB) with a Westinghouse WDPF distributed control system (DCS).

The most difficult demand of the 1990 Clean Air Act is the control of Nitrogen Oxides (NOx). The traditional solution is to replace the burners with Low NOx burners, involving a capital investment exceeding $9 million.

Naturally, before engaging in such expense, the managers searched for a less costly alternative that would fully utilize the true, latent capability of the current equipment. They chose to use D.O. to optimize the boiler combustion performance.

D.O. was started manually (in a stand-alone mode) to get an early understanding of the possible improvements and savings through optimal process adjustments. Eventually it was integrated with the DCS to automate data transmission and thus facilitate maintaining optimal running conditions[15].

Objectives/Outputs

The translation of the general business objectives into specific measurable objectives/outputs -- the Game Plan or Optimization Focus -- for optimizing the combustion at full load (235 MW) was:

1. NOx emission (measured by continuous in-situ instruments in the stack) was originally to be minimized; and when it became clear that regulations could be satisfied, changed just to be lower than a management-specified upper constraint.
2. Boiler Efficiency (a calculated value based on various measures), to be maximized.
3. Steam temperatures, to be within constraints to maintain the integrity of the turbine.
4. Stoichiometric O2, to be within constraints as dictated by past practices to maintain efficiency. Since efficiency already was to be maximized, these constraints were not truly necessary, but culturally needed for the peace-of-mind of engineers in a start-up environment.
5. A quasi-economic objective function was created to balance the total benefits of the multiple maximization objectives.

Inputs

The engineers and operators selected, based on their own knowledge and experience, the following control (decision) inputs – that were most likely to provide improvements if adjusted better -- from the many adjustable inputs which were available to them:

1. Oxygen (O2) trim, a bias correction to a theoretical curve to indicate the target excess combustion O2 measured at the stack, which determines through first-level controllers the

[15] For more details see Krueger and Patterson (1997).

amount of air delivered for the combustion for the coal necessary to deliver the desired load (MW).

2. Nine sets of dampers to distribute secondary/auxiliary air, each set adjusted with the same values.

Burner tilts, another set of possible control (decision) inputs were kept constant in the data shown here. All other adjustable control inputs were kept constant at their best-known values. Uncontrolled inputs, such as coal characteristics and atmospheric conditions were ignored, thus contributing to unexplained variations in outputs, what is called “noise”.

Future Game Plan formulations may refine the optimum by also including these variables.

The amount of coal used, controlled by the targeted load through first level control systems, was a “ruled input” used only to calculate efficiency.

While technically there are no limits as to how many inputs the D.O. technology can handle, for the sake of orderly optimization in a controlled environment it is seldom desirable to get started with more than a dozen or so inputs. The inputs can be expanded (and contracted) as we learn more about the process.

Results from Dynamic Optimization

The values of the two main outputs, NOx and Boiler Efficiency, for 106 sequential re-adjustments every hour or so, are displayed in Fig. 4.

In about 110 hours of operations, without requiring initial process data or process models, the NOx was reduced from about 0.58 lb/BTU to about 0.45 lb/BTU, and simultaneously efficiency was increased from about 89% to 92%.

The stoichiometric O2 to maintain boiler efficiency was well within the traditional constraints, and thus was consistent with conventional awareness.

The turbine safety temperatures were also generally within constraints and consistent with conventional awareness, but a few runs did go beyond constraints, and D.O. corrected this in the near future.

These results were achieved largely by reducing the excess O2 from about 3% to 2%; and by increasing the air distribution to the top burners, increasing less the air distribution to the lower burners, and reducing (making lean) the air in the middle burners.

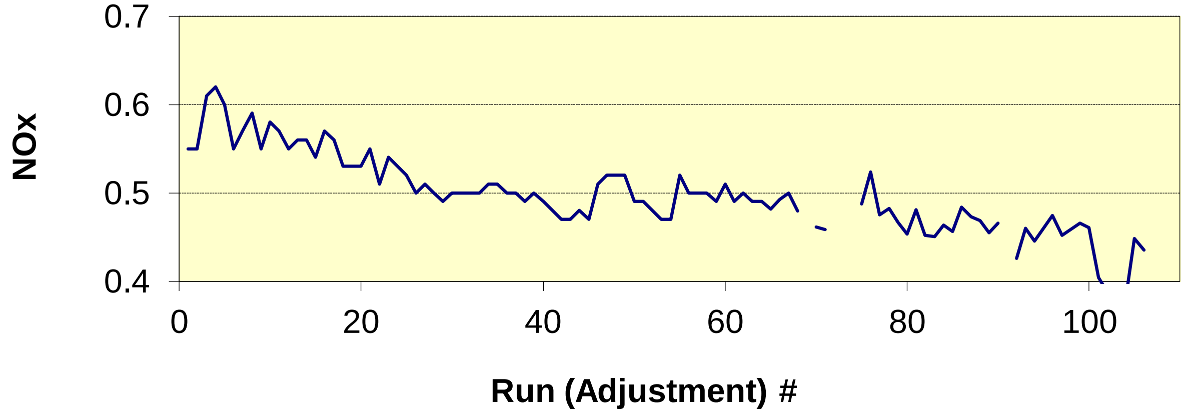
Bottom Line

All these results satisfied the Clean Air Act legislation, and avoided $9.4 million in capital expenditures for low-NOx burners.

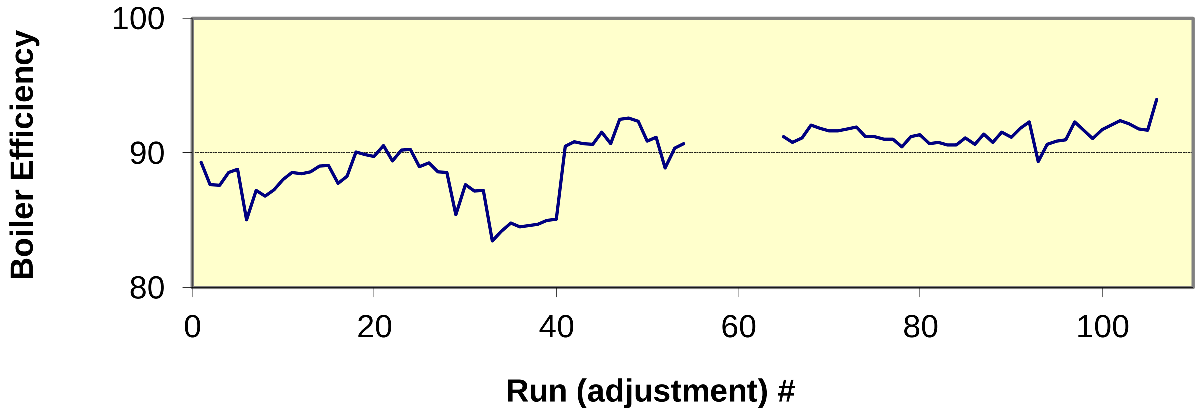
The improved efficiency resulted in fuel savings in the order of $300 K/year.

The process was always capable of these results; all that was needed was a means to adjust the process better.

Illinois Power has installed Ultramax’s D.O. in all of their fossil-fired generating units.



0.7
0.6
0.5
0.4
NOx
0
20
40
60
80
100
Run (Adjustment) #



100
90
80
Boiler Efficiency
0
20
40
60
80
100
Run (adjustment) #

Bibliography

Adelman, A., and W.F. Stevens (1972). "Process Improvement by the 'Complex' Method," AIChE Journal, Vol. 18, No. 1, p. 20.

Bhateja, C.P. and C.W. Moreno, (1989) "Practical Optimization of Production Grinding Systems", SME Modern Grinding Technology Clinic, October 10, 12, 1989; Detroit, Michigan

Box, G.E.P., and N.R. Draper (1969). *Evolutionary Operations*, John Wiley & Sons, New York, New York.

Box, G.E.P., and N.R. Draper (1987). *Empirical Model Building and Response Surfaces*, John Wiley & Sons, New York, New York.

Box, M.J. (1965). "A New Method of Constrained Optimization and a Comparison With Other Methods," Computer Journal, Vol. 6, p. 42.

Boyle, R.J., Pech, J. and Patterson, P.D. (1995), "Reducing NO_x While Maintaining Boiler Performance at TVA's Johnsonville Steam Plant Using Sequential Optimization", International Joint Power Generation Conference, Minneapolis, Minnesota, October 9-11, 1995.

Catasús-Serviá, J.J., Smoak. R.A., Squires, R.T., Baldwin, A.L., and Sorge, J.N. (1993) "A test for an Optimization Method applied to Controlling NOx Emissions in a PC-Fired Boiler", Joint ISA, POWID/EPRI Controls and Instrumentation Conference, June 7-9, 1993, Phoenix, Arizona.

Dharmarajan N.N. and P.D. Patterson, “Boiler Tuning with SPO: Critical First Step in NOx Compliance Strategy of Central & South West Corporation”, paper presented at AWMA Conference and Expo., Nashville, TN (1996).

Draper, N., and H. Smith (1966). *Applied Regression Analysis*, John Wiley & Sons, New York, New York.

Eakle, D.L., E.P. Payson, and C.A. Jarc (1997). “An On-line Advisory System Using Dynamic Optimization Enables Allegheny Power to Improve Boiler Efficiency, Reduce LOI and Control NOx”, presented at the International Joint Power Generation Conference and Exposition, Denver, CO (November 1997).

Higazy, M.A. and R.L. Haman, “Boiler Tuning Using SPO at Detroit Edison”, EPRI Workshop/NOx Controls for Utility Boilers, Cincinnati, OH (1996).

Howard,J.W. (1997). “The Effect of Dynamic Modeling and Optimization Technology on SNCR Performance”, Conference on Selective Catalytic and Non-Catalytic Reduction for NOx Control, Pittsburg, PA

Hurwitz, Arnon M. (1993) "Sequential Process Optimization with a Commercial Package", Arizona State University; 6th National Symposium: Statistics and Design in Automated Manufacturing, Phoenix, AZ, February 1993.

Krueger, M.S. and Patterson, P.D. (1997) “Optimization Saves Money, Reduces NOx” Power Engineering, Vol 101, No. 09, September 1997, pp21.

Krueger, M.S., Stopek, D.J., and Patterson, P.D. (1996), “Continuous Combustion Optimization to Improve Boiler Efficiency and Control NO_x at Illinois Power’s Hennepin Station”, Heat Rate Improvement Conference, Baltimore, September 21-23, 1998.

Lang, R and Jarc, C.A. (1998) “Using Closed-loop Dynamic Optimization to Improve Boiler Efficiency at Chemopretrol’s Litvinov Plant”, Int’l Joint Power Generation Conference, Baltimore, Maryland, Aug 24, 1998.

McVay, M. and Patterson, P.D. (1998) “Illinois Power’s On-Line Dynamic Optimization of Cyclone Boilers for Efficiency and Emissions Improvement”, Int’l Joint Power Generation Conference, Baltimore, Maryland, Aug 24, 1998.

Moreno, C.W. & Yunker, S.B. (1992) "ULTRAMAX: Continuous Process Improvement through Sequential Optimization", EPRI.

Moreno, C.W. (1979). "A Performance Approach to Attribute Sampling and Multiple Action Decisions," AIIE Transactions, September, pp. 183-97. (another example of sequential decision analysis`)

Moreno, C.W. (1984-1987) *"ULTRAMAX User's Guide"*, Ultramax Corporation, Cincinnati, Ohio, USA.

Moreno, C.W. (1986). "Self-Learning Optimizing Control Software", Instrument Society of America, Robotics and Expert Systems Conference (Robexs'86), Houston, Texas, June 1986, pp. 371-377.

Moreno, C.W. (1988). "Statistical Process Optimization," P-Q Systems Annual Conference, Dayton, Ohio, 1987, pp. 1-14.

Moreno, C.W. (1993) "How Modern 'Smarter Not Harder' Technologies can Simultaneously Maximize The Combination of Pollution Reduction and Business Success", Conference on Environmental Commerce, CONEC'93, Chattanooga, TN, October 17-20, 1993.

Moreno, C.W. (1993) "Improving Process Performance: Which is Better, Sequential Process Optimization or DOE?", Conference on Industrial Statistics and Quality Improvements, Oakland University, Rochester, MI, August 20-22, 1993.

Moreno, C.W. (1995) "*Maximizing Profits through Production. The ULTAMAX Method: Concepts and Procedures*" Ultramax Corporation, Cincinnati, Ohio, USA.

Moreno, C.W. and Redlinger, S.E. (1993), "Applications of Sequential Optimization in Injection and Blow Molding Operations", *3rd. International, Conference on Advances in Polymer Processing,* Cincinnati, Ohio, March 29-31, 1993

Moreno, C.W. and Yunker, S. B. (1992), "ULTRAMAX: Continuous Process Improvement Through Sequential Optimization", presented at EPRI, Palo Alto, Calif., 1992.

Moreno, C.W. and Yunker, S.B. (1993), "Reducing NO_x Emissions and Improving Boiler Efficiency Using Synthetic Intelligence", Conference on Expert System Applications for the Electric Power Industry, Phoenix, Arizona, December 8-10, 1993.

Nachtsheim, C. J. (1987). "Tools for Computer-Aided Design of Experiments", *Journal of Quality Technology*, Vol. 19, No. 3, July 1987, pp. 132-160.

Patterson, P.D. and Yunker, S.B. (1995), "Simultaneous Reduction of LOI and NO_x while Maintaining Boiler Performance Using Sequential Optimization", U.S. Department of Energy Unburned Carbonaceous Material on Utility Fly Ash Conference, Pittsburgh, Pennsylvania, March 1995.

Press, S.J. (1972). *Applied Multivariate Analysis*, Holt, Rinehart & Winston, Chicago, Illinois.

Redlinger, S.E. (1988). "The ULTRAMAX Method and Practical Applications", P-Q-Systems Annual Conference, Dayton, Ohio, June 15-17, 1988, pp. 2-24.

Sachs, E.M., R. Guo, S. Ha, and A. Hu, (1990), "On-line process optimization and control using [run-by-run] sequential design of experiments", *1990 Symposium on VLSI Technology Rec.*, Honolulu, HI, June.

Sachs, E.M., R. Guo, S. Ha, and A. Hu, (1991), "Process Control System for VLSI Fabrication", *IEEE Transactions on Semiconductor Manufacturing*, Vol. 4, No. 2, May 1991 Abstract

Schott, J., M. Prince and C. Jarc, "NOx and Heat Rate Reduction on Gas-Fired Boiler using ULTRAMAX", presented at EPRI Workshop/NOx Controls for Utility Boilers, Cincinnati, OH (1996).

Spendley, W., et al. (1962). "Sequential Applications of SIMPLEX Designs in Optimization and EVOP," Technometrics, Vol. 4, pp. 441-61.

Stuckmeyer, K. and R. J. Boyle (1996), "Optimization of Cyclone Boiler for NOx Control." Presented at EPRI Workshop/NOx Controls for Utility Boilers, Cincinnati, OH

Teetz, R. and Patterson, P.D. (1994), "Reducing NO_x While Maintaining Boiler Performance Using Constrained Sequential Optimization", EPRI Fuel Oil Utilization and Management Workshop, Clearwater Beach, Florida, October 1994.

Wald, A. (1947). *Sequential Analysis*, John Wiley & Sons, New York, New York.

Walters, F.H. et al. (1991). *Sequential SIMPLEX Optimization*, CRC Press, Inc., Boca Raton, Florida.