Comparison of two well known Methods for Optimizing Power Plant Operations

44th Annual ISA Power Industry Division Conference
Orlando, Florida, USA, July 7-13, 2001

Part II

ULTRAMAX's Sequential Optimization vs. Neural Networks

Carlos W. Moreno

carlos.moreno@ultramax.com

110 Boggs Ln, Ste 325
Cincinnati, Ohio, USA 45246
www.ultramax.com

Comparison of two well known Methods for Optimizing Power Plant Operations

44th Annual ISA Power Industry Division Conference

Orlando, Florida, USA, July 7-13, 2001

Part II

ULTRAMAX's Sequential Optimization vs. Neural Networks

Carlos W. Moreno carlos.moreno@ultramax.com

UMAXvsNN.doc

Abstract

The object of this paper is to provide a perspective related to the selection and expectations from various suppliers of on-line automatic supervisory control technology for the purpose of combustion optimization.

This perspective is from a person well acquainted with ULTRAMAX's Sequential Optimization, familiar with the principles of Neural Networks, and superficially acquainted with the specifics of various commercial offerings in Neural Networks (NN). The companion presenter, Mr. Parikh of Pegasus, provides Part I, an in-depth description of NN but no publication.

The main conclusions are:

- **ULTRAMAX's Sequential Optimization** yields improvements much faster, creates less production cost and disruption (bad production to gather necessary data for NN), requires less manpower, responds faster to changes in the process, and cost less (all this by a factor of about one-fifth); while
- **Neural Networks** is more thorough, it is usually offered with a lot of engineering expertise, and it could yield better results after six months if the process is stable. If the cumulative value added eventually exceeds that of the ULTRAMAX solution, this may happen after one or two years[1].

General working statements

Combustion performance in a boiler depends on the equipment and its state, on the conditions under which it runs (fuel, ambient, load, soot accumulation, etc.), and on the adjustment of control inputs (e.g., O2 bias, damper positions, etc.).

For every-day operating decisions the equipment is fixed and the conditions are defined elsewhere. What production personnel and/or optimization logic can manage on a daily basis *to produce more value* is to change the adjustment of the control inputs to compensate for current conditions and to learn by experience how to deliver more value. This is an aspect of "supervisory control", "level-2 control", and what in control theory, depending of the reference, is solved through "optimizing control" technologies.

Better business value is defined by management, and can include effects such as NOx, Heat Loss, LOI, ash quality; plus working within constraints -- fixed or variable depending on other variables -- to reflect safety, capacity, equipment life (reliability) and regulatory requirements. These change with time.

The working of Neural Networks is explained by Mr. Parikh.

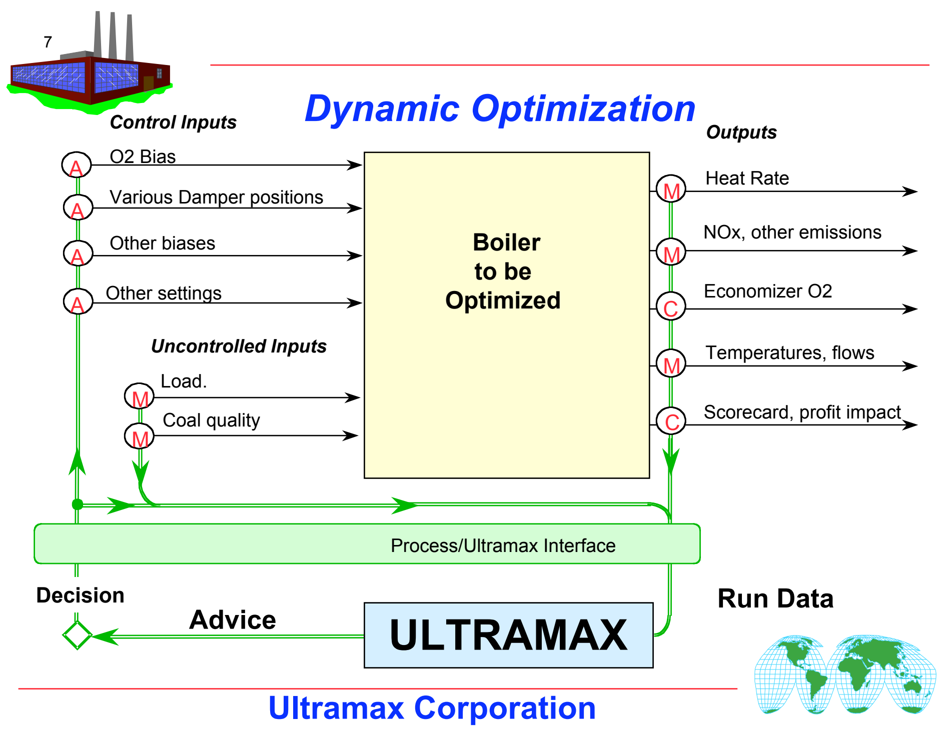
The following comments relate to an abstraction of various NN solutions being offered. Any one of the offerings may have different specifics. A user needs to understand the differences in NN solutions, as well in other services offered by the suppliers.

[1] This conclusion is an estimate, not backed up by field study comparisons.

Definitions

Data Point; Run data set	A set of combustion input and output variable values, including conditions
Control inputs; Adjusted (set) inputs	The variables that can be set in the control panel, such as biases, setpoints, and control logic coefficients (e.g., gains such as P,I,D constants, thresholds, etc.); or in some cases that are physically adjusted directly by hand.
Conditions	The uncontrolled, external inputs (load, coal quality, ambient conditions), including the scenario (burner and mill configuration)
Global optimum	Optimal combustion for a given set of conditions, the one that generates the greatest value, as achieved with the current equipment by making the optimal adjustment to the control inputs. As conditions change, there are different global optima.
Local Optimum	For a given set of conditions, a set of adjustments such that any combination of small changes in adjustments will generate lower business value; it is the “global optimum” restricted to a subset region of possible control input adjustments. Thus, the global optimum is a local optimum, but there may be several local optima of which (usually only) one will be the global optimum.

Basics of ULTRAMAX’s Sequential Optimization



Elements of Sequential Optimization

Setup:

- Define objectives, including constraints on inputs and outputs for satisfactory operations
- Define the necessary input and output variables to be adjusted (set) or measured
- Test that the process is sufficiently consistent (that outputs are reasonably repetitive for the same inputs, that noise is reasonable in comparison with possible improvements).

Sequential Optimization:

- Get improvements by implementing the following **cycle**:
  1. Adjust the control inputs (biases, setpoints, direct adjustments of dampers, etc.)
  2. Run the process until getting representative data for the outputs that are a consequence of the control and uncontrolled inputs.
  3. Transfer input/output data into the Sequential Optimization software
  4. The software generates Alerts, status statements on the progress of optimization, and an Advice with relatively small readjustments for the next cycle.
  5. Go to #1.

  Such sequence of adjustments increases combustion performance to near a local optimum for the current load, conditions and scenario. With adjustments every half-hour, starting with no prior data and no process models, 80% of the potential improvements through better adjustments is obtained in about 100 trouble-free operating hours.

What the software does every time that new combustion operating data is entered is:

1. the data is accumulated with older run data
2. Learn: using all the accumulated data, update prediction models for each output as a function of all inputs
3. Advise: using the models, create an advice for readjustment of the inputs by searching for a relatively small variation on inputs that will yield overall predicted improvements and/or data for better future models.

In particular notice how information in new operating data is used right away to decide how to best run the boiler. By comparison, the traditional approach is to collect hundreds of data points for a few months through Parametric Studies, and when completed, create models to be used to estimate optimal running conditions. Thus, the information in the data is not used for a long time, and this is a waste of existing assets.

With NN, in the need to cover a lot of operating conditions in order to finding better local optima, the process is being run very poorly many times and for a long time, this representing an important but often ignored cost.

Some NN implementations are updated periodically with new data to refine the models, where the models remain valid when the characteristics of the boiler do not change due to new equipment or major maintenance.

So, a limitation of Sequential Optimization is that it will stop in a local optimum near the starting point, while NN will be able to determine several local optima in the region covered by the data, and thus potentially better performance in the long run.

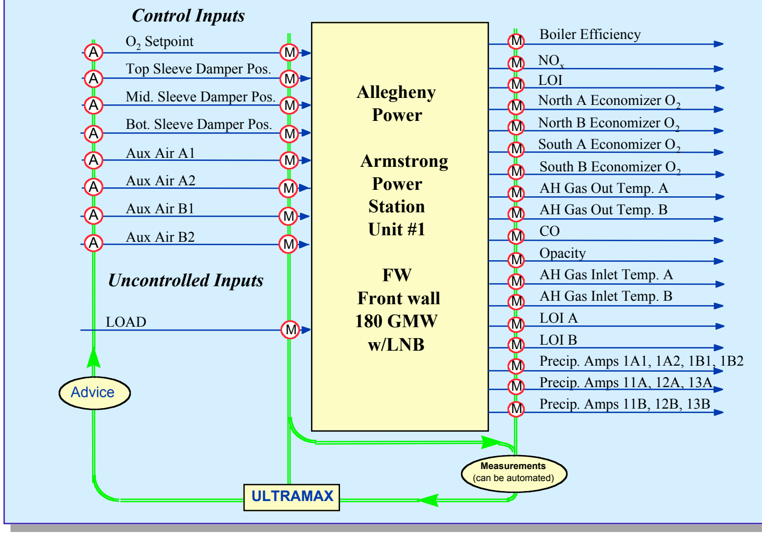
The first appendix presents this information in a table format, and the second contemplates the potential synergism of NN and Sequential Optimization.

Following is one example among many in Power Generation.

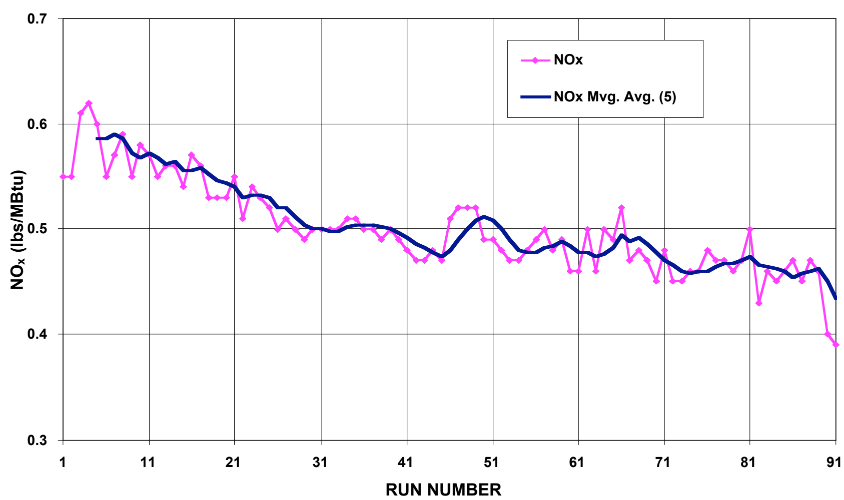
Finally there is a Summary of the characteristics of both solutions and the needs that they satisfy best.

Optimization Plan

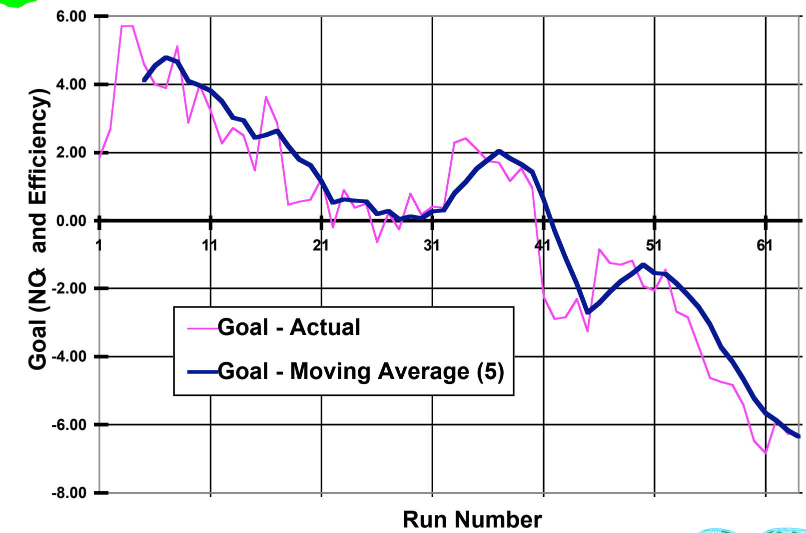
Decision Diagram



31



Ultramax Corporation


6.00
4.00
2.00
0.00
-2.00
-4.00
-6.00
-8.00
1
11
21
31
41
51
61
Goal (NOx and Efficiency)
Run Number
Goal - Actual
Goal - Moving Average (5)

Outstanding Features

NEURAL NETWORKS (NN)	ULTRAMAX's SEQUENTIAL OPTIMIZATION
Better for **interpolation**	Better for **extrapolation** (into regions without data)
So, **need widely spread operating data** in order to be able to interpolate into all reasonable optima. Recall that each combination of operating conditions (load, coal quality, etc.) has its own global optimum.	**No starting data required.** It gets started with just current running conditions, and will converge to a near-by local optimum through sequential, gradual adjustments. This is provided by the on-line sequential learning and optimization technology.
Will find the true **global optimum** only **if** it is within the region of data coverage. For those NN using only historical operating data this is a very severe limitation.	Will find a **local optimum anywhere it is,** even if never experienced before. Will do so as conditions change, and will remember data so as to approach that optimum quickly when the similar conditions repeat themselves. If there is only one local optimum, it will be the global optimum.
Obtaining the running data with the desired coverage, the "Parametric Test", is **expensive** in terms of expert manpower, and also in terms of poor performance -- high emissions, low efficiency, and potential wear-and-tear.	For a few days the process is run with the same operator-defined input adjustments (replicates) to test how consistent production outputs are, thus there are **no poor performance costs** and much lower other costs.
It takes **three to six months** to collect the data and **then** identify and implement optimal adjustments.	Local optimal adjustments are approached in about **100 hours** of operations in each load range. Requires a sufficient level of process control and consistency in outputs that about 1/3rd of the boilers do not have outright. In many cases the problems are solved quickly, and if not, optimization will take longer (more data redundancy).
Some NN solutions refine their models on-line with new operating data. However if there is a large change in operations characteristics, the old data is not longer valid, and operating data for a new parametric test needs to be collected. Changes could be due to new equipment or major maintenance.	Since Sequential Optimization models have many fewer coefficients than NN models, they can adapt to new operating characteristics much faster. Further, this technology automatically detects and "forgets" older data when it is no longer valid. That is, the models and optimization are **more dynamic**.
MORE THOROUGH **MORE ASSUREDNESS OF EVENTUALLY BEING AT A GLOBAL OPTIMUM FOR A STABLE PROCESS**	**SIMPLER** **FASTER** **HIGHER CUMULATIVE VALUE ADDED DURING THE FIRST YEAR OR FOREVER** **LOWER COSTS**

APPENDICES

Some technical characteristics

This analysis relates only to the learning and optimization technologies. In particular it does not address the significant benefits and costs of the expert combustion engineering services that various NN solution providers deliver (when they claim benefits of NN they include the benefits from this expert consulting). The offering of Ultramax Corporation builds on locally existent expertise to add the optimization know-how and tools.

The following analysis presumes that the procedures for each solution are implemented well.

Neural networks	ULTRAMAX's Sequential Optimization
It is based on the paradigm of: (1) collect a lot of data; (2) create prediction model; and (3) use the model to optimize.	It is based on the paradigm of Sequential Analysis, where after each new process run the data is used to update models and the consequent more refined predicted optimum. It does not require data, process models, or a special model structure to get started. It starts optimizing right away, and gets consistent improved results within a few weeks. Being able to model and optimizing right away is achieved through the use of Bayesian Statistics.
The models have <u>more coefficients</u> (weights) and can fit process characteristics better when there is a lot of data redundancy. In particular, it can <u>interpolate</u> more accurately than the simpler models used by ULTRAMAX[2]. The NN models fit equally well the optimal running conditions and the not-so-optimal ones.	The models are locally accurate quadratics, that have <u>fewer coefficients</u>. This is sufficient because ULTRAMAX uses the principle that to optimize one only needs sufficiently accurate models around the optimum. Further, this avoid the distortions created by trying to fit data far from the optimum, where prediction accuracy is not necessary. One benefit of fewer coefficients is that the models can <u>extrapolate</u> better into regions of no past data. Another benefit is that in case of process changes, it can catch up with the new reality with much less data, that is, quicker. Locally accurate models are created with weighted regression.
	Probably requires more consistent process behavior than NN. Otherwise, it will need lots of data like NN. This requirement helps plant personnel to become aware of problems and point to problem resolution early on, before much data is collected.
More thorough understanding of multiple optima within the data coverage, if data density is sufficient (it takes a few months to collect so much data).	Not as thorough, but will quickly get (a few weeks) to the local (perhaps global) optimum.

[2] …when used for optimization. When used only for prediction there are theoretical reasons as to why the ULTRAMAX modeling technology could provide more accuracy than NN.

Potential Synergism between NN and ULTRAMAX

For customer desirous to engage in the most thorough solution, there is a potential of getting the benefits of both NN and Sequential Optimization.

1. Before doing the Parametric test, use ULTRAMAX as an accelerator to get quickly to a local (perhaps global) optimum. Then, every other shift, run the Parametric Test to collect the necessary data (frequently far from any optimum), and the next period run ULTRAMAX to maintain the local optimum and keep management more satisfied.

   The data obtained with the Parametric test and with ULTRAMAX will be available for both the NN solution and for the ULTRAMAX solution. With the same data both the NN and ULTRAMAX will identify the global optimum, but when there are several local optima (for the same conditions) the NN solution is likely to be more accurate more often.

2. After implementing NN (with or without using ULTRAMAX as an accelerator), and using this data for ULTRAMAX, apply Sequential Optimization cycles when ULTRAMAX discovers that an optimum lies outside of the range covered by the existing data, and thus get to the corresponding local (perhaps true global) optimum.

   This possibility could be used to reduce the spread of data required with parametric testing to assure covering the optima, and thus get higher cumulative value added.

ULTRAMAX Literature

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., Stopek, D.J., and Patterson, P.D. (1996), "Continuous Combustion Optimization to Improve Boiler Efficiency and Control NOx at Illinois Power's Hennepin Station", Heat Rate Improvement Conference, Baltimore, September 21-23, 1998.

Moreno, Carlos W. (1994) "Gaining Control of Plastic Forming Machines with new Technology for On-line Adjustments" Structural Plastics Conference, April 10-13, 1994, Washington, DC.

Moreno, Carlos W. (1995-2001) *Maximizing Profits through Production,* published by Ultramax Corporation, Cincinnati, Ohio, USA, Jan 2000.

Moreno, Carlos W. (1999) "Improvements Through Process Adjustments" American Statistical Association 1999 Quality and Productivity Research Conference, May 19-21, 1999, Schenectady, New York, USA.

Moreno, Carlos W. (2001) "Dynamic Optimization of Production Operations" IIE Annual Conference 2001, May 20-23, Dallas, Texas, USA.

Patterson, Peter D. (2000) "Obtaining Reduced NOx and CO using Advanced Empirical Optimization on Boiler Operated in Load-Following Mode." Electric Power 2000 Conference, April 5, 2000, Cincinnati, Ohio, USA.