

# ***Optimization in Production Operations***

## ***Optimal “Lean Operations” in Manufacturing***

By Carlos W. Moreno

© 2005-06 [Ultramax Corporation](#) Oct. 5, 2006

### **Introduction**

This essay deals with production / manufacturing operations: with their economic impact (or other metrics) while making product with the existing process, usually driven to satisfy:

- *market demand* (delivered: volume, quality)
- *economics* (incurred: cost savings, resource utilization); and
- *safety* (safeguarding equipment, personnel and environment)

These drivers represent the main impact of production on company profits, with short-term and long-term effects on the P&L Statement.

***The bottom line is that most production processes are underutilized; and the use of mature, accessible mathematical technology unlocks that latent capacity, which is of significant value.***

The best possible performance is “**Optimal Operations.**” In the process industry it is called “**Process Optimization.**” In manufacturing it is the extreme of **Lean Operations**, one of the components of “Lean Manufacturing” success. Other components that qualify for “lean” in the sense of avoiding waste (non-value-added), and not missing opportunities for improvements are: “Lean Design” (the most common emphasis today), “Lean Logistics – and Supply Chain,” “Lean Maintenance,” “Lean Scheduling,” “Lean Safety,” and “Lean Scheduling.” Some share interests with Six Sigma as well (quality and costs).

All these solutions are also part of the classical field of Industrial Engineering in production / manufacturing, now with refined awareness, approaches and tools. The IE discipline maintains its focus on overall corporate goals; more “systems approach” than focusing on indicators of success such as: zero downtime, zero defects, lowest unit cost, zero inventory, minimize Non Value Added time, etc.

In particular, this essay focuses on the management of industrial, repetitive or continuous, bulk or discrete, high volume production operations. In most production operations it is possible to define objectives quantitatively very well, which leads to the possibility of (true, quantitative) optimization solutions. Fortunately, the problem is so generic that there are various commercial software of wide applicability to aid or automate operating decisions to optimize performance: the ultimate Lean Operations. The practice is more frequent in large continuous processes such as paper mills, power generation, chemical processes; but it has

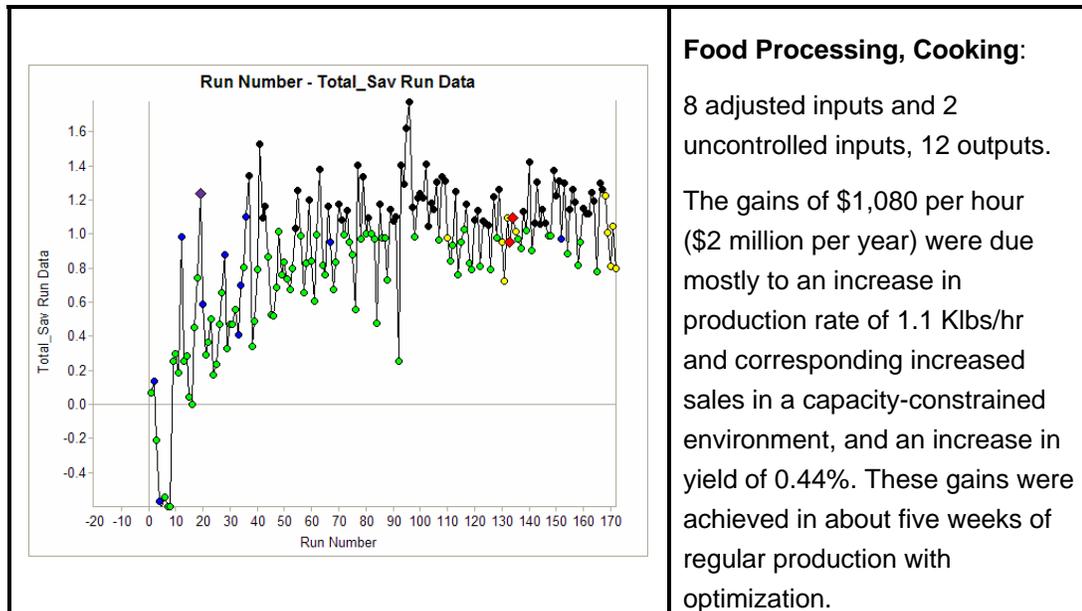
been applied very profitably to discrete manufacturing in the last decade as well, mostly for optimization studies rather than on-line.

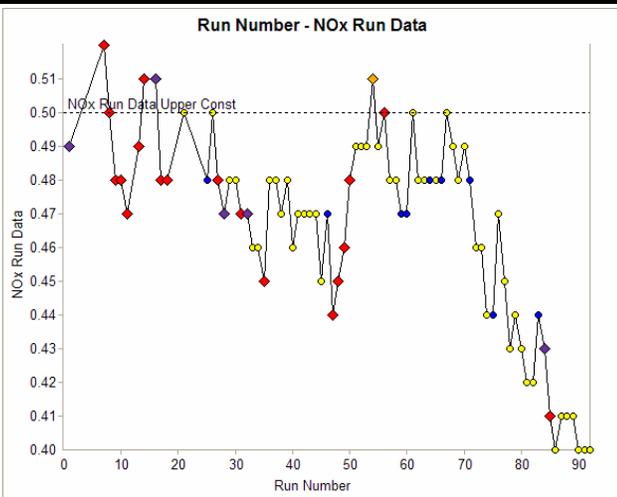
“Regular” operations (excluding startups, shutdowns, changeover, cleaning) account for the great majority of the time on the production floor, where even modest but persistent gains can have a cumulative significant impact on the P&L Statement. Tangible, measured gains from regular operations optimization are typically in the order of several \$100K to a few million dollars annually per process – see examples on the next page. Personnel also develop more understanding and have more fun.

These concepts are of interest to Corporate Production / Manufacturing Executives and Plant Managers.

### Examples of Improvements

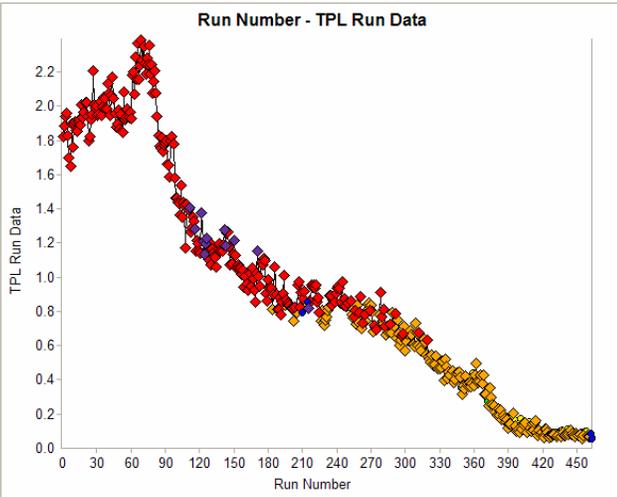
These are rather simple gains that can be harnessed from operations (with the existing production assets), just by better operating decisions. It takes the right culture, tools, and management leadership.





**Power Plant Boiler**

10 adjusted inputs, 18 outputs.  
 In addition to the 18% reduction of NOx, the primary objective, as shown in the graph, Heat Rate was reduced 0.22%, CO was reduced 95% and LOI (Loss on Ignition) was reduced 62%. Optimization still to be reached.  
 This fulfilled the EPA requirements at that time.



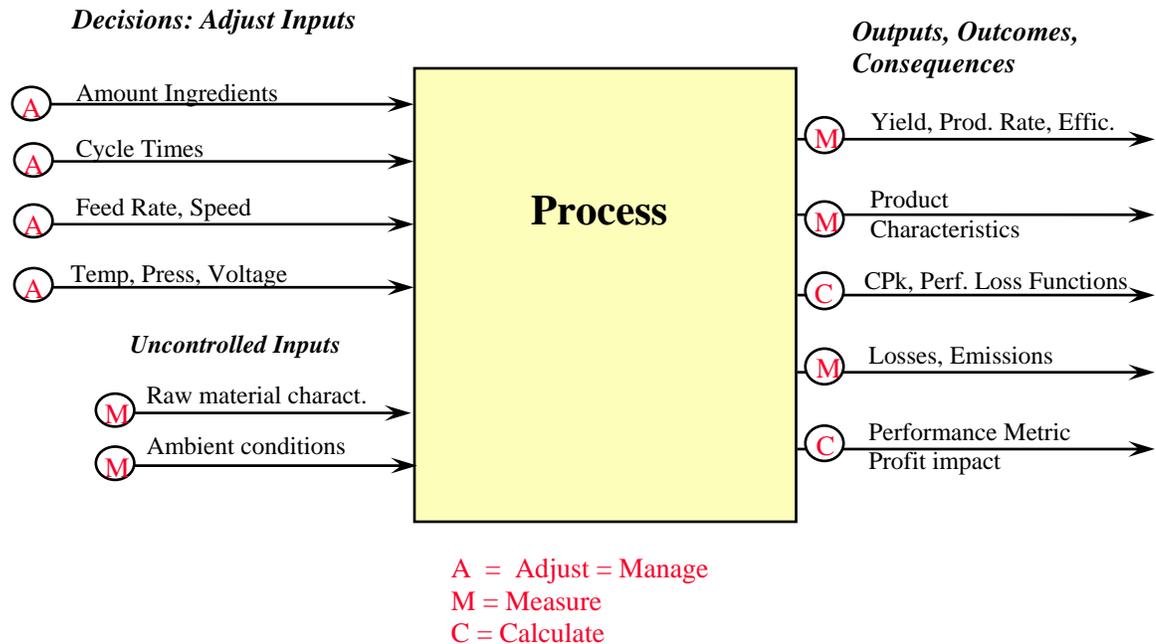
**Large process**

40 adjusted inputs, 50 outputs.  
 The Performance Metric was a Total Performance Loss metric (TPL) to be minimized representing 44 business considerations, including throughputs and quality targets.  
 The frequent red diamonds (not the orange) up to run 200, were as the optimization system learned how to obey many constraints (more important than TPLs) which were violated to start with.

## Production and Improving Performance

Let us look at a generic process operation:

### *Operations Management Elements*



Production / Manufacturing operating performance is managed by the adjustment of adjustable inputs (decisions made). These adjustments are usually of setpoints for regulatory process control (typically knobs in the control panel) and physical position of things (e.g., a baffle in a duct). If there is built-in logic to re-set setpoints according to conditions, those settings can be refined by the adjustment of "biases". The best possible performance with existing production assets is achieved by the best possible adjustments: altogether, the **optimum**, which depends on the values of the uncontrolled inputs.

Production Operations management is an area of interest to: (1) Plant Management; (2) Industrial (or Systems) Engineering (the main area of expertise of the author); and (3) Process Control engineering. So, the focus of this report is a point of convergence for these three fields.

## Aspects of Production / Manufacturing Operations

### ***Measurements of Performance***

To evaluate improvements one needs performance metrics. Optimization is to achieve the best possible performance metric(s) within a particular scope of interest.

Key Performance Indicators (KPI) are the main parameters necessary to evaluate performance in manufacturing (equivalent to Kaplan's and Norton's "Balanced Scorecard.")

In production / manufacturing operations, performance is determined by:

- Constraints on decisions and outcomes that should not be violated, e.g., safety / reliability limits, capacity limits, quality specifications, government regulations.
- A Performance Index which is a single, overall, composite metric of all KPIs impacts (relevant when constraints are satisfied); an actual or proxy for variable profit impact.

For outputs beyond direct regulatory process control, the Performance Index can include a "cost" for deviation from targets, thus making optimization also perform "regulatory process control" balanced with other objectives. It can also include a "cost" for standard deviations.

The Constraints and Performance Index need to be sufficiently holistic or comprehensive to avoid the syndrome of appearing to achieve improvements when there are actually higher losses elsewhere – as happens with some frequency. This is consistent with a "Systems Approach" to production / manufacturing operations management.

### ***Scope of the Operations***

The specific **Scope** of regular operations optimization is defined by: the variables (parameters) to be used (adjusted inputs, measured uncontrolled inputs, outputs and KPIs, and the Performance Index), Constraints on inputs and outputs, and evaluation calculations.

Optimal adjustments often depend on conditions which may not remain constant, such as:

- a. raw material and/or fuel characteristics (melting point, density, pH, impurities, moisture, amount of fat, fuel caloric content and hardness)
- b. decisions made outside the scope of optimization: which process components are operating (coal mills, sprayers in a tower), demand (speed, load on a boiler)
- c. environmental conditions (ambient temperature and moisture)
- d. state of the process (temperature of cooling water, time since cleaning filters or renewing catalytic agent)
- e. business requirements (quality specifications, max unit cost, min production rate)
- f. economic conditions: cost of materials / fuel (useful when there are potential substitutions); demand to use the process for other products (its marginal value); demand for the product (marginal value of extra production in a capacity constrained environment)

The first four are physical conditions represented by “uncontrolled inputs” for each batch or production run. The last two are business conditions represented by factors in evaluation calculations or KPI constraints.

Different optimal adjustments for different physical conditions is called “compensation”; and for different business conditions is called “responsiveness” or “agility.” These two can be key mechanisms for higher overall performance, productivity and profitability, e.g.:

- Depending on the water content of the raw material the best performance is likely to have a different level of drying, to save energy costs when possible and achieve balanced impact in other evaluations.
- Depending on whether at any one time business is “sales constrained” or “capacity constrained” the best performance will either emphasize unit cost reduction in the former or the right amount of higher production rate at increased unit cost in the later.

In dynamic solution technologies the scope can be refined as the user develops a sharper awareness of what is important for the firm -- a highly desirable outcome of optimization leading to a better understanding of the business and a legacy of maturity for future operations personnel.

### ***Process Control and remaining Noise***

Typical process control systems include:

- Basic “**regulatory process control**” to maintain various controlled variables close to the setpoint decisions as the process is subject to perturbations or instabilities. This is implemented with various (single) feedback control loops, or multivariable with dynamic matrix control (DMC) or model predictive control in Advanced Process Control (APC). The best possible is “Optimal Regulatory Process Control,” and this is NOT “Optimal Operations,” which also depends on the values given to the setpoints.
- Sometimes, built-in “**control logic**” to adjust setpoints as a pre-set mathematical function of various physical conditions. These are “rule-based,” static, partial and virtually never optimal – even if called “optimization.”

Normally, several important process outputs (e.g., KPIs) are not directly under regulatory control (e.g., yields, NOx in the stack, losses, most quality attributes and costs). To modify them one needs to alter the adjustment of inputs, which in turn will affect all other outputs, a multivariable challenge.

**"Noise"** is the unexplained variation in output data, e.g. for constant values of adjustments and known physical conditions. Noise is created by: inherent variations in the process (including imperfect regulatory control), sensor inaccuracies, and unknown changes in physical conditions. Noise usually affects the optimal adjustments so that data with noise does not violate constraints.

Thus, up to a point, anything that reduces noise, such as with Advanced Process Control (APC), is an improvement in its own right and it enables better operations optimization.

### **About Improvements and Optimization**

There are three "levels" of improvements:

1. Implementation of better decisions (not applying optimization), resulting in sub-optimization.
2. Implementation of optimal solution(s) to a reduced scope (e.g., subset of possible decisions, subset of the process, and/or subset of alternate objectives). This results in sub-optimization.
3. Implementation of the best solution for the full scope (full optimization).

Level No. 2 sub-optimizations usually produce decisions **different** than full optimization (e.g. [http://pespmc1.vub.ac.be/ASC/PRINCI\\_SUBOP.html](http://pespmc1.vub.ac.be/ASC/PRINCI_SUBOP.html)). However, it can give the **same** (or substantially similar) optimal sub-set decisions in what is called a "separable" scope. Any optimization scope is a sub-optimization to a larger scope. Being able to identify "separable" optimization scopes is a good skill to aid in management and simplicity.

### **Optimization Solutions / Technologies**

It is interesting to note that the problem of Operations Management Optimization (Lean Operations) is sufficiently **generic** and there are several commercially available softwares with fairly broad applicability -- with the appropriate training and culture. In fact, some suppliers do not offer process expertise, just optimization know-how. This is a sign of maturity for the tools and methods, and good news to production executives and engineers. They are the ones to decide whether to reach this level of proficiency in the plant. Also, the technologies are a bridge between production, manufacturing, and fabrication. They are "advanced decision support" and "process analytical" technologies.

Optimization – obviously a quantitative procedure -- requires the application of discipline and serious multivariable mathematical technology. There are three main optimization technologies used: (1) First-Principle Models, (2) Sequential Empirical Optimization, and (3) Neural Networks. In general, they have this in common:

- They depend on the good performance of the Regulatory Control System
- Each application requires the formulation of a Scope to drive the software

- For each output there is a prediction model as a function of all the inputs (the decision adjustments and uncontrolled)
  - There is an optimization engine to search the prediction models for the best combination of adjustment decisions that result in the best predicted performance metrics, given the values of the uncontrolled inputs (if any). The effectiveness of optimization depends on the accuracy of the models around the optimum.
1. First-Principle Models: Prediction models are created based on fundamental laws of nature through mathematical simulations (physical, chemical, etc.), and may be complemented with coefficients determined empirically. Then they are validated empirically with production operations in the area of combination of inputs (adjusted and uncontrolled) of perceived interest.

First-principle models reproduce how nature behaves. This is the basic approach learned by engineers in school, and indispensable for equipment design. They need to be kept up to date as various changes are made to the process.

2. Sequential Empirical Optimization (SEO): It starts at the current process adjustments and without any data or models. Then one applies the following optimization cycles every hour or batch length:
  - With the process: make adjustments (the Advice from the previous cycle), run production operations, collect consequent operating run data
  - With the software: enter new run data, update models (with new data) and generate new Advice for adjustments (by searching the updated models).

These cycles extrapolate and converge rather quickly towards the optimum while engaged in productive manufacturing / production.

SEO reproduces conceptually the process of a person learning how to perform better a repetitive task as he/she gets more practice and experience. So, it applies to systems that run repetitively or continuously.

SEO is started in “Advisory” mode where plant personnel need to approve the “Advices” generated by each cycle. As SEO learns and plant personnel trust it, they can turn “Closed-Loop” on. It can also be used for engineering studies; for instance, it optimizes static SOPs, much more effectively than Design of Experiments, DOE.

SEO was first developed at Procter & Gamble in the early 70's to adopt the advantages of sequential learning and analysis promoted by Wald (1947) and partially implemented by EVOP and Simplex in the '60 to overcome the problems with DOE. The main business drive was to improve the profitability impact of production / manufacturing. [Bibliography](#)

3. Neural Networks (NN): Start by collecting experimental operating data with a large coverage of combinations of adjusted and uncontrolled inputs; and then fit the very versatile NN models to the data. Models are valid in the region covered by sufficient data. The models cannot be based on historical data because it is very unlikely that sufficient combinations took place around the optimum.

NN reproduces how knowledge is presumably stored in the network of neurons and dendrites in a brain. The main characteristic of these models is the ability to fit convoluted – but smooth – nonlinearities, excellent to represent production processes. NN were developed to the point of optimization in the 80's.

4. Design of Experiments (DOE): Start by collecting production data in a highly structured combination of experimental adjustments, to which a mathematical model is fitted for each output (in most cases one need more than just linear models). Models are valid in the region covered by sufficient data; and in this region they are best at understanding the individual effects of inputs on outputs (which is not, in fact, necessary for empirical optimization).

DOE was formalized first by Fischer in '35 and response surface methodologies (RSM) applied in computers since the 60's. The '60 also saw a heuristic based optimization: Simplex.

Empirical solutions (#2, #3 & #4) look at how the process actually behaves, limited by the noise (lack of consistency). First-principle models (#1) are limited by the lack of thoroughness of the simulations – and insufficient if unable to predict some KPIs.

The best solutions are the ones that have the best prediction models. Also, there is a great variety of actual and hidden costs of creation and maintenance (e.g., empirical models created up-front require many bad production runs for data). Each solution has advantages and disadvantages as in this table:

Main Advantages	Main Disadvantages
<p><b>First Principle models</b></p> <ul style="list-style-type: none"> <li>• Creation of the models requires thorough understanding of the process fundamentals, which will aid resolving future problems and generating ideas to improve the process</li> <li>• Can be used for prediction, and can recognize several local optima, in the whole region of inputs where the models are valid</li> <li>• Applications not dependent on measuring output values</li> </ul>	<ul style="list-style-type: none"> <li>• It takes a lot of expertise and time to develop and validate the models (while the process continues running at baseline) – if the models can be created at all.</li> <li>• Models are static (or updated by a few coefficients)</li> <li>• Quality of models is limited by lack of accuracy in the representation of all important behaviors within the process.</li> <li>• It only interpolates; it cannot find the optimum if outside the area where models were validated</li> </ul>
<p><b>Sequential Empirical Optimization (SEO)</b></p> <ul style="list-style-type: none"> <li>• The fastest technology to obtain improvements and approaching the optimum. It is also the simplest.</li> <li>• SEO cycles <u>extrapolate</u> towards the optimum without requiring prior experience near the optimum (it also interpolates). Faster and better extrapolation than updated NN because it has many fewer coefficients.</li> <li>• Dynamic, scope can be changed easily at any time. Very easy to restart after changes in equipment.</li> </ul>	<ul style="list-style-type: none"> <li>• It requires continual collection of good quality operating data to maintain automatically the dynamic models. As an advantage, this enables detecting upsets, sometimes before alarms sound.</li> <li>• Quality of models is limited by the noise in the output data</li> <li>• May end up in a local optimum if any exists in the right location</li> <li>• Models predict accurately only around the optimum; achieved by avoiding the distortions created by fitting data elsewhere (but that is all which is necessary for optimization)</li> </ul>
<p><b>Neural Networks (NN)</b></p> <ul style="list-style-type: none"> <li>• Models are good for prediction in the whole area where experimental data was collected – which also determines where the models are valid</li> <li>• Can recognize several local optima (in the whole region of inputs where the models are valid).</li> <li>• Applications not dependent on measuring output values (there are exceptions)</li> </ul>	<ul style="list-style-type: none"> <li>• It requires collecting a large set of experimental production data up front. This is time consuming and especially disruptive (costly) by incurring very poor operating performance (including constraint violations)</li> <li>• Quality of models is limited by the noise in the output data</li> <li>• It mostly interpolates; it cannot find the optimum if outside the area where models are valid; but models could expand if updated with sufficient data.</li> </ul>

Optimization solutions are provided by several suppliers dedicated only to optimization; and also by several suppliers of Instrumentation, Automation and Control (but the latter tend to call many other solutions “optimization”, which in our scope are simply improvements or sub-optimization).

## **Conclusion**

The management of repetitive or continuous industrial production / manufacturing operations is of such nature that operations optimization of existing production assets is realistic and practical, yielding the ultimate Lean Operations. There are software solution tools which are generic and can be implemented on top of the process control systems, making production with optimization truly accessible. Such solutions regularly yield over 100% ROI, while annualized gains of over one million dollars per production process are not unusual.

Further, the understanding of optimal solutions and of barriers to higher performance helps discover economical changes to the process to further increase profits (recall, not only cost-cutting); which in turn will be optimized and this macro-cycle of improvements and innovation repeated.

## **About the Author:**

Dr. Carlos Wm. Moreno is the CEO and Founder of Ultramax Corporation in Cincinnati, Ohio. Since 1982 Ultramax Corporation has been providing industry with the most effective technology for managing production / manufacturing operations (with existing facilities) to maximize economic gains through quality, productivity, cost and emissions operating performance.

For fourteen years before that, Carlos was a corporate internal consultant within the Procter & Gamble Company in the areas of production and development with particular emphasis on production and product optimization, economic analysis and quality control. He developed innovative technical solutions in the above areas that have been published in professional and trade journals and in books. He has taught graduate courses at Bradley University, Xavier University, and the University of Cincinnati, mostly in the areas of operations research and quality control.

### Education:

Ph.D. in Industrial Engineering from Purdue University,  
M.S. in Mechanical Engineering from CALTECH,  
B.S. in Engineering Science from the Case Inst. of Tech.

### Memberships:

Fellow of ASQ (American Society for Quality).  
Senior member of the IIE (Institute of Industrial Engineers),  
Member ISA (Instrumentation, Systems and Automation society)

Ultramax Corporation

*Advanced Process Management™*

[www.ultramax.com](http://www.ultramax.com)

110 Boggs Ln. Ste 325

Cincinnati, Ohio 45246, USA

(513) 469-8629