Optimization in Production Operations

Optimal "Lean Operations" in Manufacturing

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Abstract

For a Production / Manufacturing process, given the process (equipment, sensors, controls, etc.), given the available adjustments to manage operations, and given the performance metrics, the process has an optimal set of adjustment decisions that produces the consequent optimal operations performance. This optimal solution is Excellence in Lean Operations. This problem is one of the few areas where the term "optimization" can be fully applied is the "best possible" in quantitative terms, an analytical (mathematical) solution. Within such structure, there are software solutions in the market that solve operations optimization.

This essay describes the scope of operations optimization including the nature of defining operating performance and the operating decisions available to improve them. Then it describes the four main technologies for solutions: First-principle models, Sequential Empirical Optimization, Neural Networks and Design of Experiments; and describes the main advantages and disadvantages of each.

The core message is that commercial solutions to production operations optimization – or Lean Operation in manufacturing -- are so mature that approaching operations optimization is today very viable.

There is an Appendix explaining in more depth the Sequential Empirical Optimization technology about which the author is most expert.

Introduction

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

- *market demand* (delivered: volume, quality)
- *economics* (incurred: costs, 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 in practice 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 frequent emphasis today), “Lean Logistics and Supply Chain”, “Lean Maintenance”, “Lean Scheduling”, “Lean Safety”. 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 I.E. discipline maintains its focus on <u>overall</u> 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.

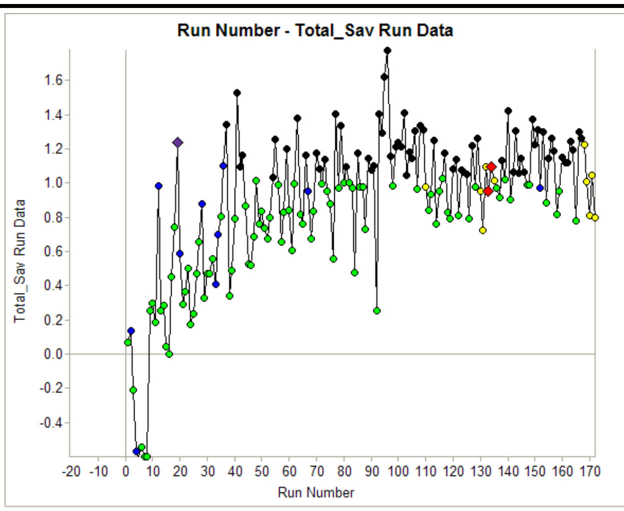
In particular, this essay focuses on the management of industrial, repetitive or continuous, bulk or discrete, <u>high volume</u> production operations. In most production operations it is possible to define objectives quantitatively very well, which leads to the possibility of (true, quantitative) optimization solutions. Fortunately, the problem is so generic that there are various commercial softwares 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 optimization.

“Regular” operations (excluding startups, shutdowns, changeover, cleaning) accounts 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 <u>per process</u> – see examples on the next page. Personnel also develop sharper understanding and have more fun.

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

Examples of Improvements

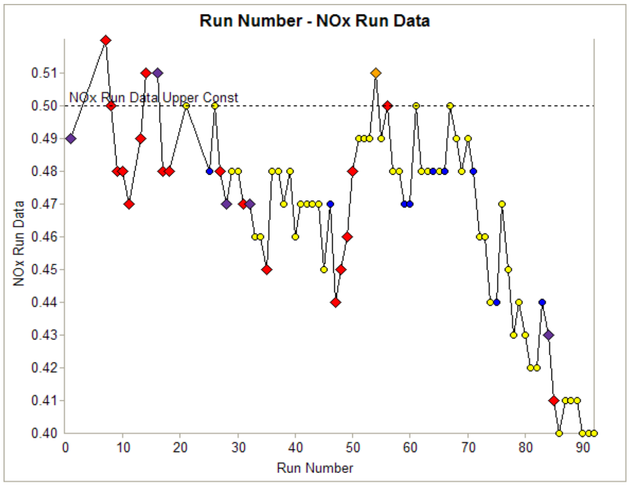
These are rather simple gains that can be harnessed from operations (with the existing production assets), just by better operating adjustment decisions; which takes the right culture, tools, and management leadership.



Food Processing, Cooking:

8 adjusted inputs and 2 uncontrolled inputs, 12 outputs.

The gains of $1,080 per hour ($2 million per year) were due mostly to an increase in production rate of 1.1 Klbs/hr and corresponding increased sales in a capacity-constrained environment, and an increase in yield of 0.44%. These gains were achieved in about five weeks of regular production with optimization.

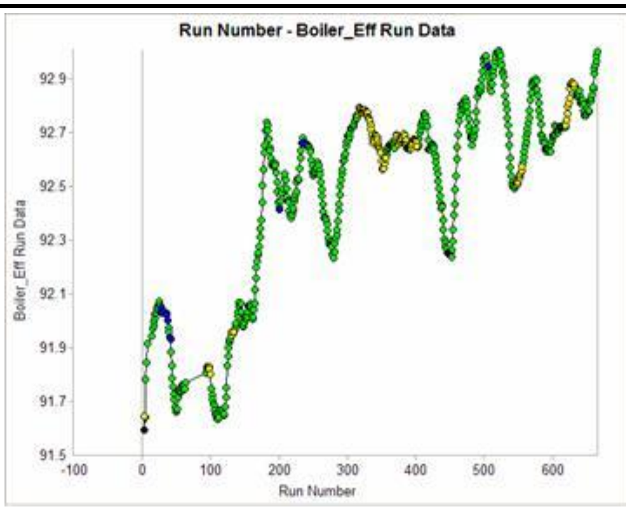


Power Plant Boiler

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.



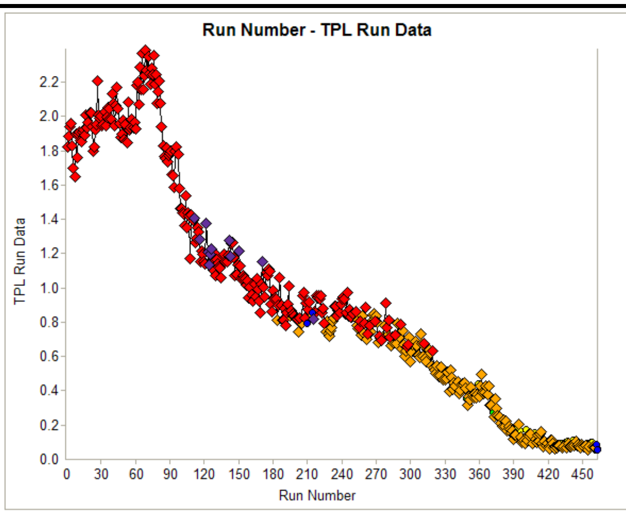
550 MW Utility Boiler

Zou-Xian, Shandong, China

5 mills, 18 uncontrolled inputs (varying coal quality), 9 adjustments (O2, dampers), 53 outputs.

Given safety / reliability considerations, the main performance objective was to maximize Efficiency.

Improvements obtained in the first 600 hours of operations.



Large process

40 adjusted inputs, 50 outputs.

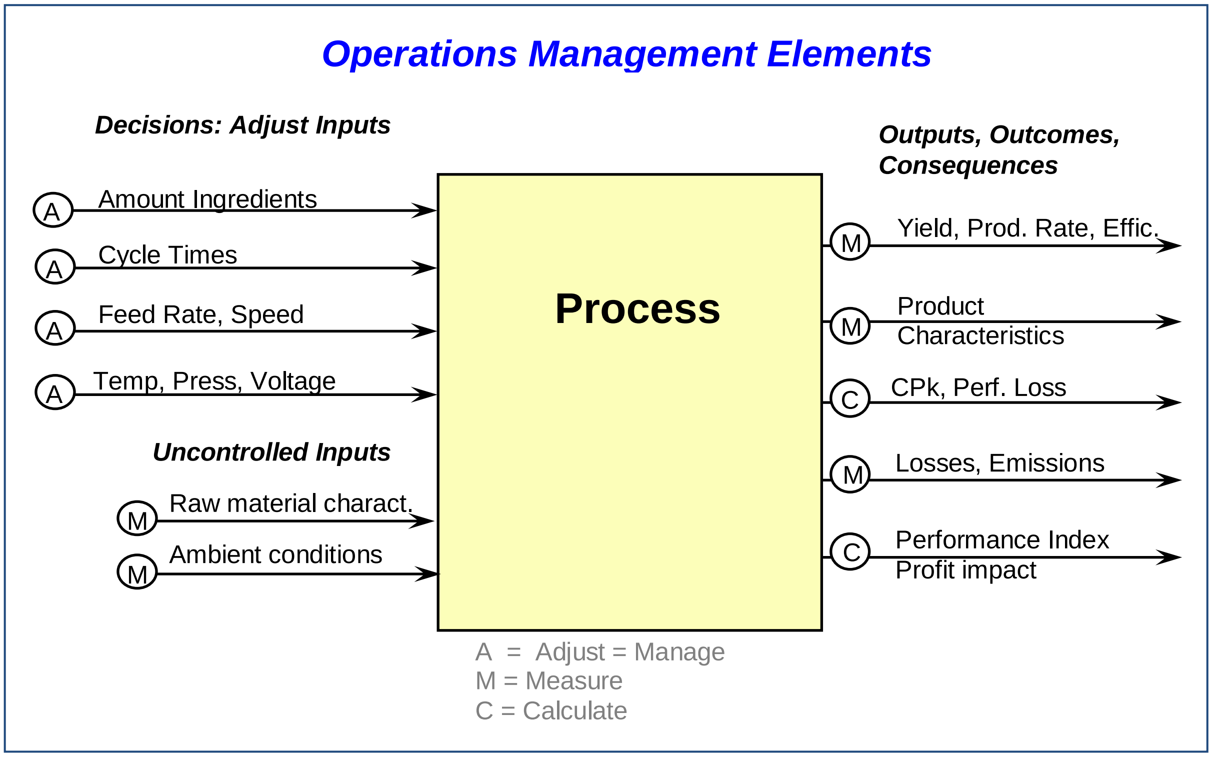
Baseline operations violated constraints, shown in red diamonds.

The Performance Metric (meaningful when constraints are satisfied) was a Total Performance Loss metric (TPL) to be minimized representing 44 business considerations, including throughputs and quality targets.

Note that it took some 250 runs to learn how to satisfy constraints (beginning of orange instead of red).

Production and Improving Performance

Let us look at a generic process operation:



Production / Manufacturing operating performance is managed by the adjustment of adjustable inputs (the decisions made); 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 supervisory logic that re-sets setpoints based on conditions (uncontrolled inputs), those settings can be refined by the adjustment of "biases". The best possible performance with existing production assets and conditions is achieved by the best possible adjustments: altogether, the **optimum operations**.

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.

In production / manufacturing operations, performance is determined by:

- Constraints on adjustments and outcomes that should not be violated to represent minimum requirements, e.g., safety / reliability and capacity limits, quality specifications, emission regulations, min. production rate, etc. They may include indicators such s KPI; and actual economic impact in the P&L Statement.

- A <u>Performance Index</u> which is a single, overall, composite metric of the operating parameters which should be maximized or minimized while maintaining reliability meeting constraints; an actual or proxy for variable profit impact in most kinds of production businesses.

  For outputs beyond direct reach of 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 non-consistency, such as standard deviations.

The Constraints and Performance Index need to be sufficiently holistic or comprehensive to avoid the syndrome of appearing to achieve improvements while actually incurring 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 such as adjusted inputs, measured uncontrolled inputs, outputs and the Performance Index; Constraints on inputs and outputs; and evaluation calculations.

Optimal adjustments often depend on <u>conditions</u> 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, hardness)

b. decisions made outside the scope of (this) optimization: which process components are operating (coal mills, sprayers in a tower), demand (speed, volume, 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 <u>physical conditions</u> represented by "uncontrolled inputs" for each batch or production run. The last two are <u>business conditions</u> represented by constraints or factors in evaluation calculations.

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

- 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 control for given setpoints is “Optimal Regulatory Process Control”; and this is NOT “Optimal Operations”, which resolves the issue of which are the best setpoint values.
- Sometimes, built-in “**supervisory control logic**” to adjust setpoints as a pre-set function of various physical conditions. These are “rule-based”, static, partial and virtually never optimal – even if called “optimization”.

Normally, several important process outputs are not directly under regulatory control (e.g., yields, NOx in the stack, losses, most quality attributes, 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 <u>unknown</u> 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 <u>and</u> it enables better operations optimization.

About Operations Improvements and Optimization

There are three “levels” of operations improvements:

1. Implementation of better decisions (not applying true 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 or alternate objectives). This results in sub-optimization.
3. Implementation of the best solution for the full scope (full optimization).

Level #2 sub-optimizations usually produce decisions **different** than full optimization (e.g. http://pespmc1.vub.ac.be/ASC/PRINCI_SUBOP.html). However, it could 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** that 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; the ones to decide whether to reach this level of proficiency in the plant. These solutions are also called “advanced decision support” and “process analytical” technologies.

(True) Optimization – obviously a quantitative procedure -- requires the application of discipline and serious multivariable mathematical technology. There are four main optimization technologies used: (1) First-Principle Models, (2) Sequential Empirical Optimization, (3) Neural Networks; and (4) Design of Experiments (DOE) and Response Surface Analysis (RSM). 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). <u>The effectiveness of optimization depends on the accuracy of the models around the optimum.</u>

1. <u>First-Principle Models</u>: Prediction models are created based on knowledge of the 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 new equipment design. They need to be more accurate for operations optimization, and need to be kept up to date as various changes are made to the process.

2. <u>Sequential Empirical Optimization (SEO)</u>: It starts at the current process adjustments and without any data or models (also called ‘tabula rasa’). Then one applies the following optimization cycles about 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 and store new run data, update models (with past and 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 all systems that run repetitively or continuously – as long as one can make quantitative decisions and measure outcomes.

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

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: www.Ultramax.com/Bibliography.htm

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. They need to be kept up to date as various changes are made to the process.

   NN were developed to the point of reliable 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 simple mathematical model is fitted for each output (in most cases one needs more than just linear models). Models are valid in the region covered by sufficient data. In that region the DOE models 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 R. A. Fisher in '35 and response surface methodologies (RSM) applied in computers since the 60's. The '60 also saw a heuristic based sequential 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 knowledge or thoroughness of the simulations – and insufficient for optimization if unable to predict some performance metrics.

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

Main Advantages	Main Disadvantages
First Principle models	
• Creation of models for all important outputs requires thorough understanding of the process fundamentals, which will aid resolving future problems and generating ideas to improve the process • Can be used for prediction, and can recognize several local optima, in the whole region of inputs where the models are valid • Regular use not dependent on measuring output values	• It takes a lot of expertise and time to develop and validate complete models (while the process continues running at baseline) – if all the models can be created. • Models are static (or updated by a few coefficients) • Quality of models is limited by lack of accuracy in the representation of all important behaviors within the process. • It only interpolates; it cannot reliably find the optimum if outside the area where models were validated.
Sequential Empirical Optimization (SEO)	
• The fastest technology to obtain improvements and approaching the optimum. It is also the simplest. • 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. • Dynamic: scope can be changed easily at any time. Very easy to restart after changes in equipment.	• 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. • Quality of models is limited by the noise in the output data • May end up in a local optimum if any exists in the right location • 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)
Neural Networks (NN)	
• Models are good for prediction in the whole area where sufficient experimental data was collected – which also determines where the models are valid • Can recognize several local optima • Regular use not dependent on measuring output values (there are exceptions)	• 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) • Quality of models is limited by the noise in the output data • It mostly interpolates; it cannot find the optimum if outside the area where models are valid; but models could be expanded if updated with sufficient data.
Design of Experiments (DOE)	
• Can predict in whole area of input data • Inexpensive software (but very limited)	• Requires collection of experimental operating data up front; disruptive • Limited by noise in output data • Only interpolates • Only for a static solution • May end up in sub-optimum area • Difficult to address multiple objectives

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. In manufacturing this yields optimal 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 is repeated.

APPENDIX

Sequential Empirical Optimization

Following are some salient features of Ultramax®, a mature tool-set in the market for optimizing the operations of regular production / manufacturing / fabrication with existing equipment. The product has the slogan "Advanced Process Management™" (APM™), and is based on the Sequential Empirical Optimization technology. It continues to be developed and distributed world-wide by Ultramax Corporation (UMC) in Cincinnati, Ohio, USA, with the original two generations creation within Procter & Gamble; but since 1982 UMC created independently the third generation. www.ultramax.com.

1. It is very automated and simple to implement. It automatically resolves the balance among any number of performance metrics – some as constraints, some as metrics to be improved after constraints are satisfied reliably. It automatically resolves re-adjustments to compensate for measured uncontrolled inputs that affect performance.

   It learns to optimize much faster than other technologies, and does not require prediction models up front, because of sequential learning and using Bayesian statistics. The only exception is already having a process model more accurate that what Ultramax can create from operating data.

   Significant improvements are frequently obtained within a few days to weeks of operations, and reach near-optimum in a few weeks to months.

2. Only 1% of the applications were to start with already at near-optimal operations. The annual gains in industrial high volume production are typically in the order of $500K/yr per process, with some frequency exceeding multiple million dollars per year. These are the latent gains available by better operations management above and beyond what the user is already generating with the existing management (and control) method.

3. Ultramax does not take control away from plant personnel, rather it significantly enhances the plant personnel management of operations, and this provides for an almost a risk-free application. The sequential Advices for new adjustments provided by the SEO cycles are not mandatory, plant personnel can easily modify them. In on-line applications (with automatic data exchange with digital process control) plant personnel can control when to be in Advisory or Closed-loop Optimization. There is also an option for Stand-Alone (manual) Optimization systems – particularly useful for optimization studies, such as to optimize static SOPs or even the design of the product and process.

4. Ultramax hovers above the DCS or SCADA, and does not interact with the process control algorithms, but sees its effects. Ultramax can work with or without any APC in place, even if the APC includes some optimization modules. Of course, if the process already has optimization with very good quality models in place, then Ultramax offers no short-term advantages.

5. The tool is dynamic: e.g., the specifics of the scope of optimization can be changed at any time, thus reflecting the increased sophistication of plant personnel with optimization. Performance evaluations can be calculated with special factors easily defined by upper management to quickly respond to changing business conditions.

   After sufficient experience, there is almost immediate compensation to changes in measured physical conditions and responsiveness to new business conditions (feed-forward). Ultramax also updates to slow changes in process behavior due to unknown physical conditions (feed-back, with a long lag).

6. Ultramax enables adding user-designed supervisory control logic or empirically based rules for adjustments. It also enables using prior prediction models (including first-principle models) and creates a correction upon them to predict process outputs more accurately at the beginning, with little data.
7. It accepts occasionally missing output data (such as when a sensor fails, until fixed) and still makes use of the other valid data.
8. What-if Analysis gives predicted values and consequent Alerts for user-defined exploratory input values.
9. Enables "Transient" optimization, e.g., as known physical conditions keep on changing
10. Ultramax detects (some) upsets before alarms sound, such as in (multivariable) Statistical Process Control (SPC).
11. Plant personnel are driven more acutely by business needs, and become sharper in discovering problems, barriers and solutions.

The examples in the main body of the essay were obtained with Ultramax; and www.ultramax.com/Applications.htm has many others.

Successful industrial applications include: Chemicals (a great variety), food processing (cooking, smoking), coffee roasting, soap / detergent, fibers, nonwovens, paper making (including energy conservation), encapsulation, machining and metal removal, boilers for steam and electric power generation (100 applications with emphasis on emissions control and fuel efficiency), fermentation (antibiotics), pigments and dyes, painting and coating, plastics (including injection molding, extrusion, blow-molding and composite materials), welding and soldering, semiconductor fabrication (photolithography, dry etching, film deposition, thermal processing and ion implantation).