The “Smart” Refinery: Economics and Technology

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THE "SMART" REFINERY: ECONOMICS AND TECHNOLOGY

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Abstract

Advances in sensors, automation, and information technology have significantly changed the way refineries operate. High performance computing in physically small devices and high speed communication technology developments have been the foundation for many of these advances. Advanced analytical and optimization methods based on this infrastructure can simultaneously lower costs, increase profitability and improve customer service across the supply chain. The collective changes are sometimes characterized as constituting "smart refining." They allow the refinery staff to better analyze the past, assess the current state, and predict future behavior under alternative scenarios. In this paper, we survey the recent history of these developments and look at likely future trends. Economic benefits achieved through implementation of this technology are explained and a framework for understanding them presented. The issues that have slowed adoption and implementation are also discussed.

Introduction

What is a "smart refinery?" We are all aware of the extraordinary developments that are occurring in the computer and communication area. It seems that almost every day there is another report of the continuing decrease in the cost and size of computing elements and the continuing increase in the availability of communication bandwidth. Advances in software and mathematical analysis have built on these developments to significantly increase our ability to model and optimize refining activities. Many new developments in process sensor and measurement devices have also appeared. These developments have led to new methods and procedures for operating production facilities. The new procedures utilize more comprehensive and frequent measurements of the current state of the refinery, increased use of models and other analytical techniques to compare what the refinery is currently producing against what is expected and to understand the differences, earlier detection of anomalous conditions, and tools to plan future operation with increased confidence. While we may be aware of these developments as individual advances, their cumulative and combinatorial aspects are perhaps less well recognized. This paper will discuss how the combination of these technologies has led to an evolutionary change in the way refineries can operate. This change is to decisions and actions based primarily on the best available *prediction* of expected future conditions rather than *reactions* principally triggered by what has just happened. This shift in focus is the defining characteristic of "smart refining."

The second related subject of this paper concerns the expected economic benefits from investments in this area. The link between technology developments and improved economic results including increased productivity is not always apparent. Many unsupportable claims on potential benefits are made. Correspondingly, there are many technology developments that are believed to be beneficial but it is not clear how to translate this belief into realistic monetary values.

Incentives for Change

Why do we need to consider these new technologies for use in refineries? What refinery problems are they solving that can't be solved more economically by other means? In answering this question, three major incentive areas are reviewed below – financial, safety and environmental issues, and workforce demographics.

Financial

Looking at overall financial performance, the five year average return on invested capital for the US refining industry for the period 1996 to 2001 has been approximately 9.5% (3) which is at or below the cost of capital for the industry with 2002 results generally lower. Individual refining companies have varied widely with five year averages that range from negative to 14% (15). Clearly there are individual differences in financial performance and competitive pressures force the industry to pursue all avenues for improvement.

Operational excellence is the goal of most refineries and this excellence has many components. Among these components are some key objectives that have a direct and significant impact on the financial performance of the site. These include:

- Produce the highest valued product mix possible
- Maximize production from existing equipment
- Maximize equipments' on stream operating (service) factor
- Continually reduce costs and pursue operational efficiencies
- Keep inventories as low as possible
- Minimize Health, Safety and Environmental incidents

where the last objective implicitly recognizes the reality that HSE issues can often be governing.

Where are the opportunities for operational improvement?

Energy – Energy costs remain the largest single cost component in the refineries after crude purchases. For the 1996 to 2001 period, they averaged approximately 8% of the value of crude purchases and about 30% of all operating costs for the overall US refining industry (3). There are many opportunities for energy savings in the average refinery that remain unpursued.

Reliability – Lost production due to unscheduled shutdowns or slowdowns of refinery equipment and process units remains an ongoing problem with average losses in potential capacity of 3 to 7%.

Maintenance – Maintenance costs are the third largest cost component after crude and energy at 10% to 20% of the operating costs but often the maintenance action is provided too early when not required and sometimes (regrettably) too late.

Inventory – Large inventories of crude, intermediates, and products are characteristic of many refineries. Excessive inventory increases working capital and reduces the return on invested capital.

The components of "smart refining" provide some of the most cost effective investments available to achieve the operational excellence objectives listed above.

Safety and Environmental Issues

The safety and environmental performance of the refining industry is widely viewed by the public as unsatisfactory. Analysis of the cause of recent accidents and incidents indicate that many factors including design, change control, and operational issues contributed to the incidents (1,2). However, reviewing the incidents and potential amelioration indicate that improved measurements and real time analysis/ detection might have prevented or at least substantially reduced the damage from approximately 25% to 50% of these accidents.

Environmental emissions from refineries continue to be a major problem. Although the US Chemical Process Industires (CPI), reduced its emissions by 56.3% from 1989 to 1999 while increasing production by 33.3% (5), it still remains the largest single US manufacturing industry source of undesirable emissions (6). Industry along the Texas Gulf Coast, which is the world's largest single concentration of CPI sites, is under government mandates to reduce NOx emissions by a full 80% by 2007 (13). Obtaining the latter goal and continuing the reduction will require many changes in refinery design and operation. Improved measurements, modeling, analysis, and control are critical to the goal of reducing emissions.

Demographics

The demographics of process refinery operators in North America are changing. With industry downsizing there was very limited hiring in the 80's and 90's. As a result, 75+% of the operators in the CPI are expected to retire in the next 10 to 15 years (13). Clearly, the average operator experience level will drop as a result. In addition, the demands for enhanced analytical skills in the operator's job are increasing. A partial solution to this problem is again to use refinery measurements, modeling and analytical techniques to automate routine decision processes or at least provide the information to make the decision process more efficient.

The general conclusion from the comments above is that there is a significant need for improved operation in the refining industry and that "smart" automation technology can be a significant contributor to the improved operation.

Prediction Versus Reaction

What is meant by decisions based on intelligent *prediction* rather than *reaction*? The concept can perhaps best be understood in the context of the normal decision process in the refinery as presented in figure 1 below. We measure a condition in the refinery or detect a change of state, analyze the data to potentially spot an anomaly, predict the effect of alternative action scenarios, decide which scenario to implement, and then actually implement the scenarios. After this, the cycle repeats. Examples of decisions made in this framework include what products to produce and when to produce them, decisions on the resources required for production including feedstocks and manpower and decisions on when to perform maintenance on a particular item of equipment.

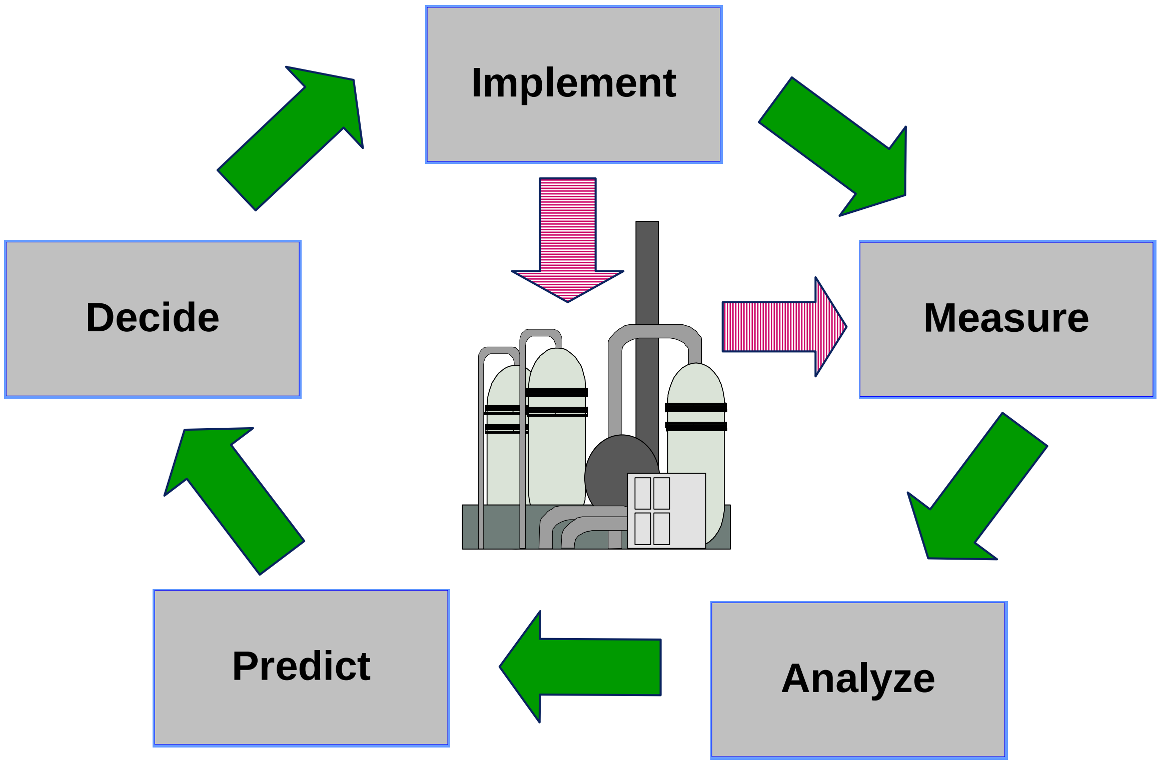

Figure 1. Refinery Decision Cycle

What are the characteristics of the steps in this process?

Measure

Modern refineries produce a lot of data. It is not unusual for a large refinery site to have 100,000 distinct measurements. If these measurements are scanned once a minute, ten gigabytes a week of data will be produced. However, the data is natively of poor quality. Instrument readings drift and noise corrupts the measurements. Even when the actual measurements are good, the statistical properties are not – the data is cross-correlated and serially auto-correlated. It is often hard to detect changes or trends.

Analyze

Analyze in this context is obtaining the best possible estimate of the current performance of the system (refinery) and its history. Generally this means processing the raw data through some kind of a model to obtain a performance indicator, perhaps of an individual piece of equipment or of the overall refinery or site. This performance indicator is then compared against a standard. The standard could be the normal, new or clean performance of the equipment; it could be the financial budget for the refinery; or it could be environmental or design limits. The model could be simply our memory of how things behaved previously or it could be a formal mathematical formulation. Key issues with analysis are to detect under (or over) performance and precursors of abnormal events.

Predict

The next step in the decision process is to project into the future the expected behavior of the system based on the information available. In some cases, this is done by simply extrapolating future behavior to be the same as current or to expect future behavior to follow the same pattern the system has exhibited in the past under similar conditions. In more complicated situations, we can use an estimate of the current state, a model of the system, and assumptions about the disturbances or effects that the system will experience. Repeating from the paragraph above, analysis refers to obtaining the best possible estimate of the current and past state of the system while prediction refers to obtaining the best possible projection of future behavior.

Decide

Ultimately it is necessary to make a decision about the action to take in the future – including no new action and no change in condition. Normally this is done by evaluating a set of feasible alternative decision sequences and then choosing one that maximizes or minimizes a combined set of objectives within the imposed set of constraints – with this evaluation and choice done within the time available.

Implementation

Implementation is the actual execution of the scenario chosen. It involves all of the activities required to make some change occur including most particularly inducing individuals in the refinery to perform or not perform an action. Without implementation, measurement, analysis and prediction are just an exercise.

The decision steps mentioned above are obviously not new and in fact have been followed in refineries for many years before computers and networks had any major impact. Those charged with decisions did the best they could at obtaining information on the state of the refinery, on estimating its current performance and predicting what would happen with various decision scenarios. However, the uncertainty levels were very high and most decisions were not analytically based.

How do we move towards "smart" operation? We can improve the overall decision process by:

- Knowing better what the refinery is doing now – this implies more accurate measurements with less delay and more frequent measurements of previously difficult to measure conditions.
- Comparing better what the refinery is doing against what it is expected to do and understanding the differences – this leads to model based analysis and techniques which promote comprehension of the information
- Predicting better the effect of alternate decisions in the future

Some examples from different operational areas may make this clearer.

Predictive Control Example

The first is from the control field. Consider the evolution from the PID controller to advanced controllers utilizing multivariable predictive constraint control (MPCC) algorithms. A standard PID loop is shown below:

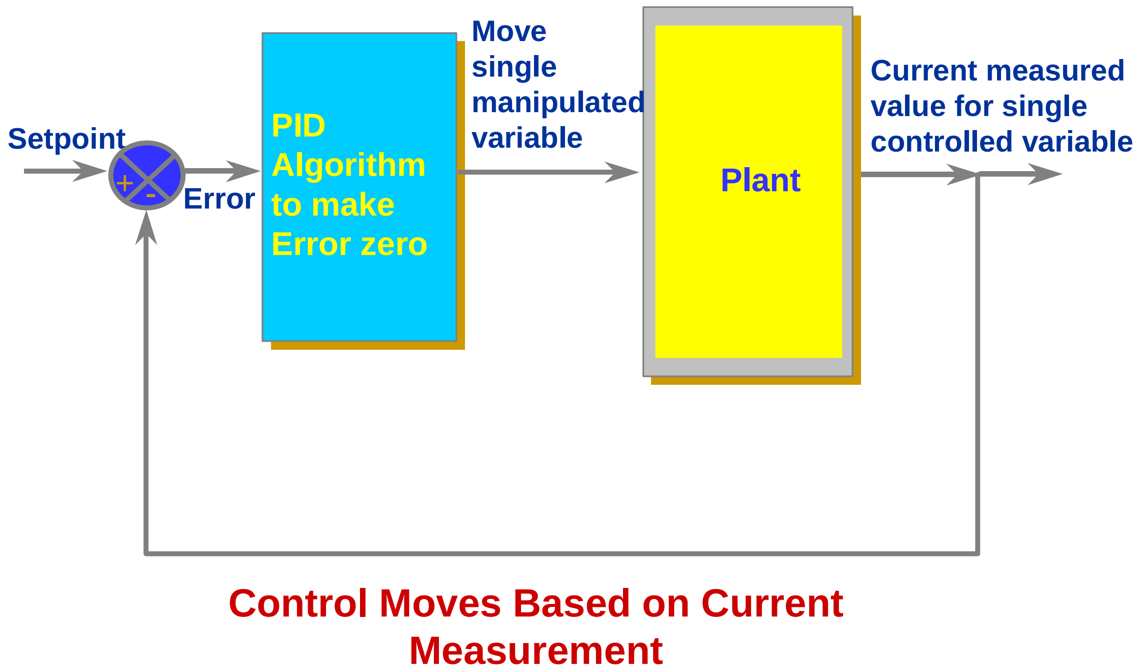

Figure 2 – Standard PID Loop

The controller senses the current measurement of the controlled variable, compares it with the desired setpoint to calculate an error, and then takes corrective action based on the parameter settings of the controller. It *reacts* to the current measurement. Contrast this with the action of an MPCC algorithm in Figure 3 following.

For MPCC, there is a formal mathematical model relating the response of the controlled variable to changes in the manipulated variable. This then allows the control algorithm to use the history and current values of manipulated and controlled variable moves to *predict* the behavior of the plant in the future and to take action based on this prediction. The controller predicts if a controlled variable is likely, in the time period of the prediction horizon, to deviate from its specification or violate a plant limit. Control action can then be taken to correct the condition before there is ever an actual deviation or violation detected. The implementation part of the decision process is done automatically via closed loop control. Moreover, we can combine the models for multiple controlled and manipulated variables into one controller that explicitly recognizes the interaction between them as shown in Figure 4 below. The result is significantly improved control performance. Reductions in standard deviation of 30 to 70% over standard PID control are routinely reported with MPCC implementation and payout period of a few months for investments in this technology are often reported.

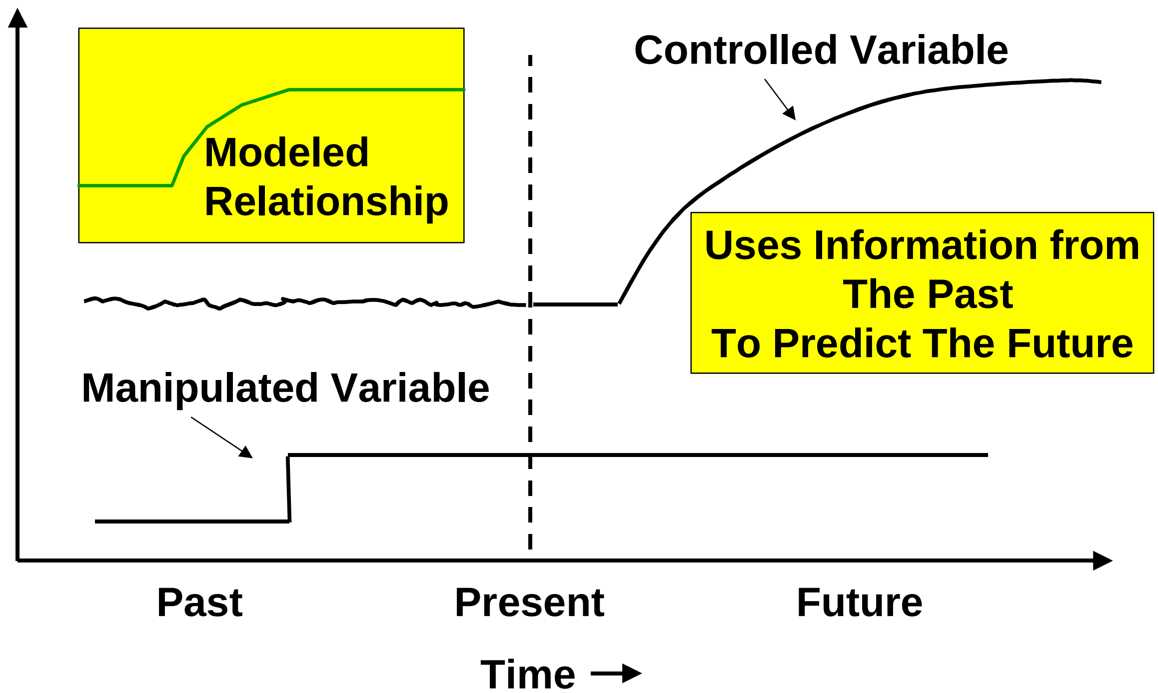

Figure 3 – Predictive Control Modeling

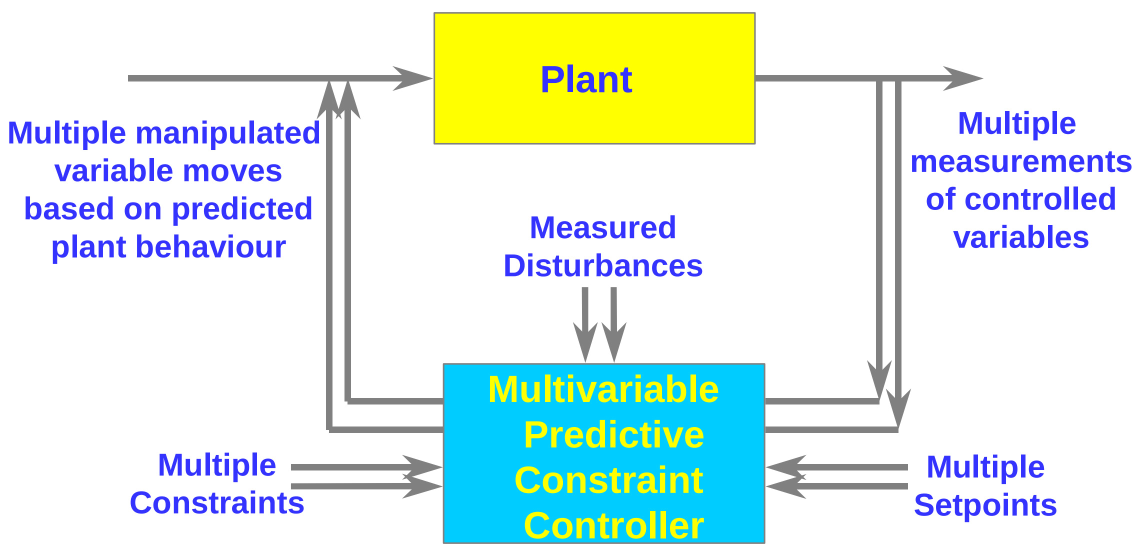

Figure 4 - Multivariable Predictive Constraint Control

Predictive Maintenance Example

The second example, from reference 18, concerns plant maintenance. There are several approaches to maintenance in the plant. One is to wait until the equipment breaks and then *react* to fix it if it is really important. Many plants still operate in this mode. The second, known as preventative maintenance, uses average times to failure for equipment and schedules maintenance before the expected failure time. However, equipment can vary widely in actual performance. *Predictive* maintenance attempts to find techniques to determine more precisely if equipment is underperforming or about to fail. With the continuing improvement in computing and communication capabilities, predictive maintenance can be based on actual device performance data, obtained and analyzed in near real time. The overall objective is to catch potential equipment problems early which leads to less expensive repairs and less downtime. Conversely, we want to avoid shutting expensive equipment down unnecessarily. Figure 5, following, illustrates the concept. Detecting anomalies early and deciding what they imply with respect to the equipment is the goal. For example, the vibration patterns of rotating equipment vary with deterioration of the equipment and can be used as predictors of failure. In operation, data from the process and the equipment is validated and brought to performance models. These calculate the performance and correct it to standard conditions. With economic information, the cost of poor performance is also calculated. This can be used for predictions of unscheduled removal (or replacement) of part(s), disruption of service, or delays of capacity. Maintenance based on this approach has been shown to reduce unscheduled maintenance costs by as much as 20 to 30% while simultaneously improving equipment reliability.

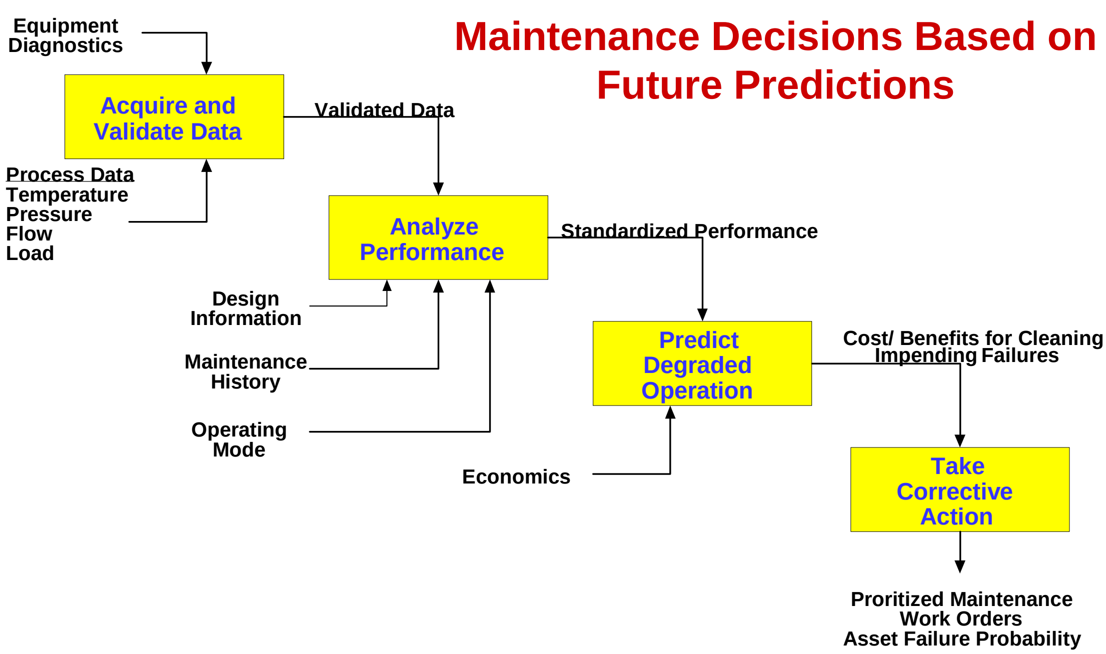

Figure 5 – Predictive Maintenance

Predictive Product Demand Forecasting Example

The staff at every refinery needs to make a decision on the quantity of each product to produce in the next production period and this decision is based partially on a forecast of market demand. It is also recognized that the forecast will always have uncertainty due to market fluctuations, production interruptions and transportation issues. The response to this uncertainty is to have substantial product inventories that ensure actual demands seldom go unmet. In fact, many refineries even today set their schedules in large measure to produce to inventory, i.e. there is a target inventory of each product and when the actual amount falls below this amount, they *react* and produce more to fill the tanks back to the desired levels. Other elements of the supply chain, i.e. production, the terminals, and the retail outlets all contain more stocks of feed and product inventory. These inventories tend to be controlled locally and set based on problem avoidance at the individual site. The result is excessive inventory in the supply chain that consumes unneeded working capital. Modern product demand forecasting systems utilize sophisticated modeling of expected demand based upon extensive analysis of historical records and correlations with demand triggers, i.e. expected weather patterns. These are combined with real time information about the current total state of inventory across the supply chain as shown in the figure below to *predict* demand and set production targets (14). Analytical analysis of the projected risk of not meeting demand compared with the cost of inventory can then be made. One oil company reported a substantial increase in profitability largely attributed to implementation of this technology (20).

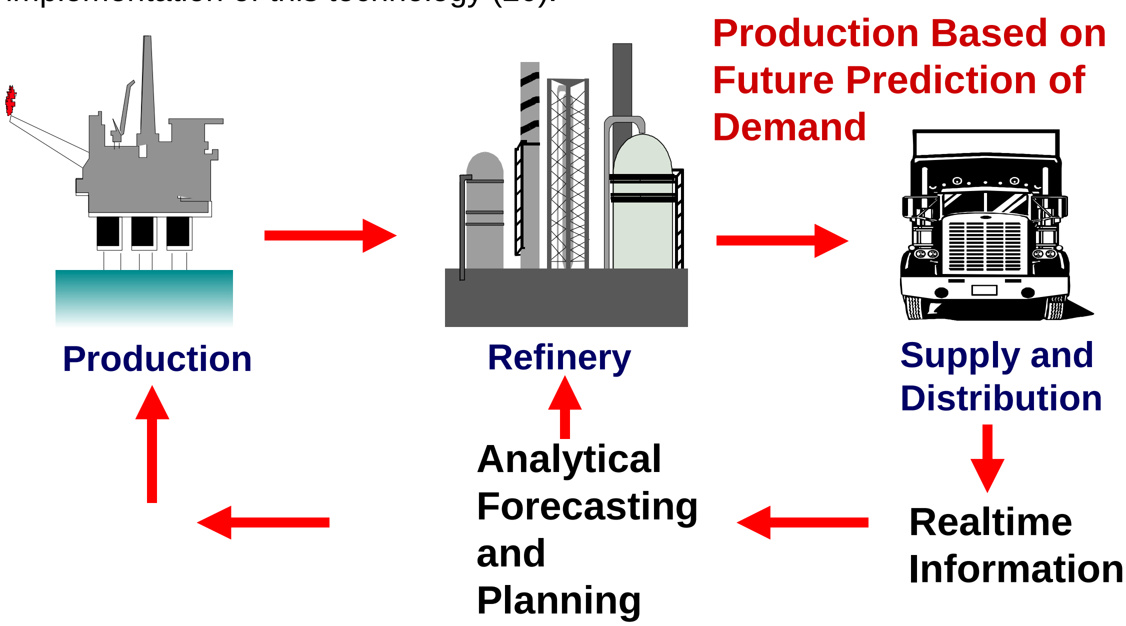

Figure 6 –Predictive Product Demand Forecasting

Enabling Technologies

What are the enabling technologies that permit refineries to move from *reacting* to *predicting*? There are certainly dozens and perhaps even hundreds of new developments that could be discussed. In the sections below, the ones that the author views as having the most important impact on operations are presented and referenced to their specific decision cycle position as shown in figure 7 below. Since space limits how much functionality can be covered in this document, some references are provided on sources for more information. The emphasis again is on the cumulative and combined effect of these developments to support the "smart" refinery operation.

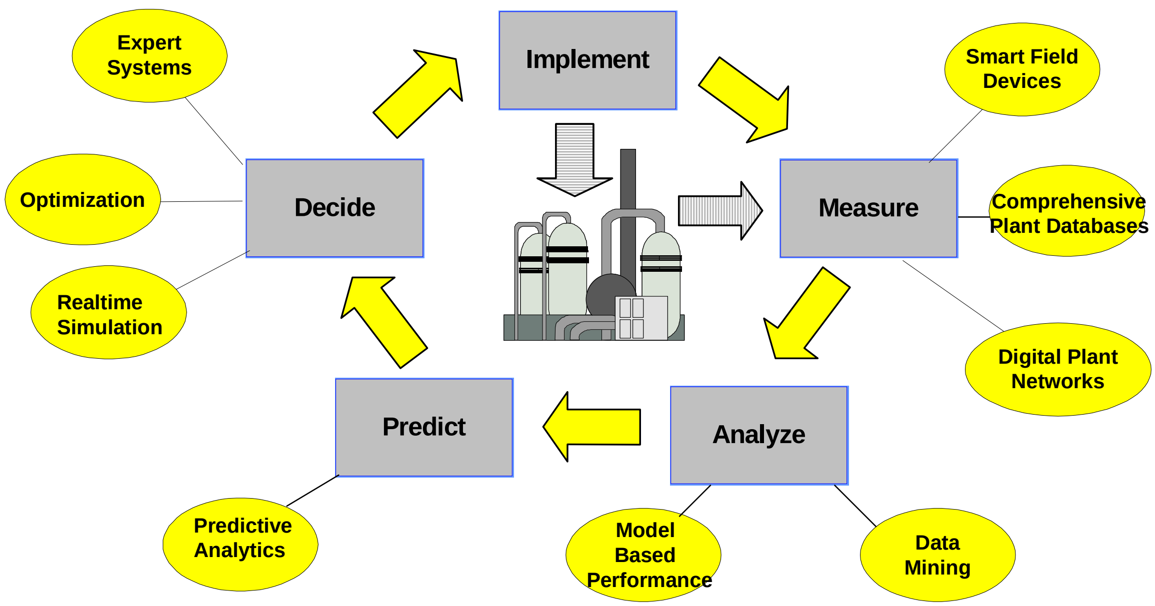

Figure 7 – Enabling Technologies

Measure

<u>Smart Field Devices</u> – One of the most dramatic technology developments has been in the general area of smart field devices. As microprocessors have shrunk, they have been incorporated directly into basic refinery equipment. In the instrumentation area, this has included transmitters, valves, and primary measurement devises including process analyzers. These devices have become in essence small data servers. A basic transmitter a few years ago would send one 4-20 ma signal back to the control system as an indication of the measured value. Today, a modern transmitter sends back multiple readings plus at least six different alarm conditions. A standard electric motor that previously had no real time measurements now has as many as fifteen sensors providing temperatures, flux, run times, etc. that are available for recording and diagnosis. Modern valves now calculate and retain in local data history a current valve signature of pressure versus stem travel, compare it with the signature when the valve was installed, and provide diagnostic information or alarming on the difference. An example is shown below in Figure 8 of a valve that is clearly malfunctioning and is reporting this malfunctioning in real time. In addition to normal measurements, cheap

sensors allowing thermal photographic and audiometric data monitoring on major equipment are being routinely used. The data transfer is not just from the devices to the central database. Configuration and calibration information is entered remotely and executed without the necessity for local activation.

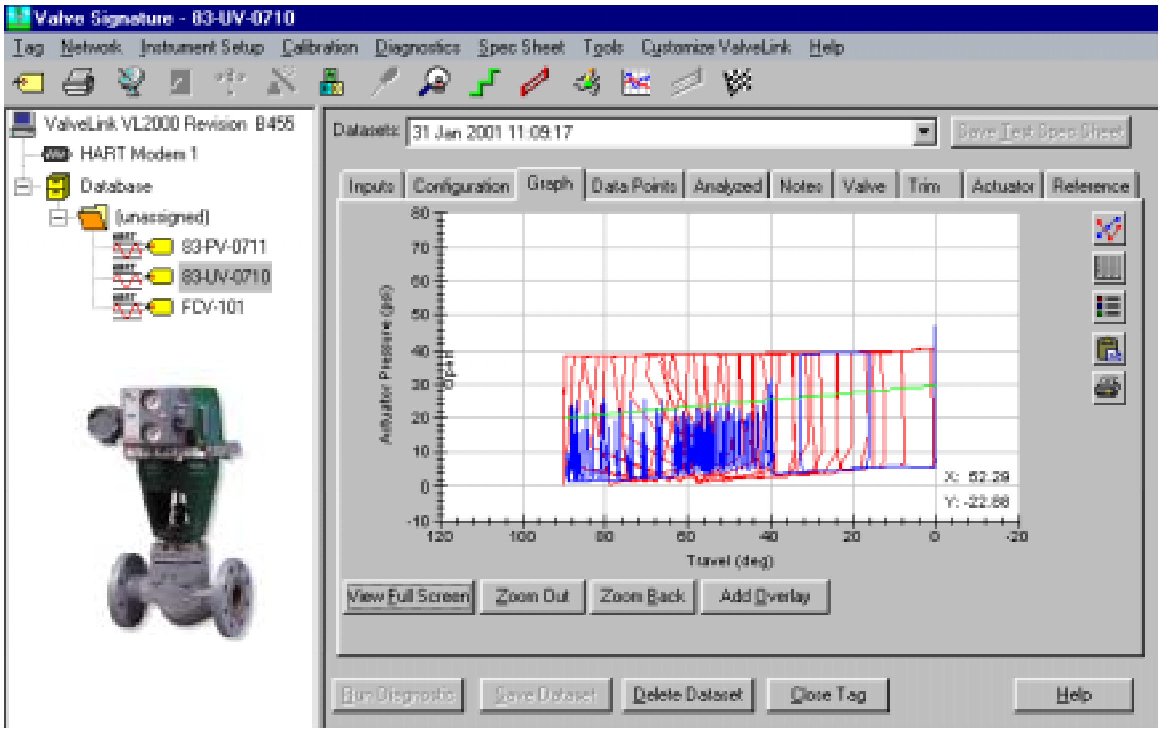

Figure 8 – Typical Smart Device

Analytical procedures that could only be performed in laboratories a few years ago are now migrating to field devices. Examples include NIR (Near Infra-Red) and NMR (Nuclear Magnetic Resonance) analyses.

<u>Digital Plant Networks</u> – Supporting the increases in local measurement and analytical capability has been a change from analog based communication for field instrumentation to digital bus structures. This produces a corresponding increase in communication bandwidth of several orders of magnitude and permits much more diagnostic information to be carried to the data system. Open standards for these buses have encouraged interoperability among devices from multiple manufacturers. Connectivity between the plant instrumentation network, the control network, and the plant IT network has also evolved into a reliable backbone for plant systems. This infrastructure is required to support the other applications that analyze and use the data. The continuing evolution in remote access through developments in the Internet is well known and will not be repeated here. What perhaps is less well known is the penetration of wireless communication into the refinery environment. Remote sensors are being installed without wires on refinery equipment where there is no need for two way communication and absolute reliability is not as important.

Comprehensive Plant Databases - Although there have been plant databases for many years, the continued evolution in their functionality has maintained their importance as the basic infrastructure or enabler for other applications. Previously they were primarily aimed at storage of realtime process data and related calculations for historical records and trending. Today there is a much larger set of information that must be maintained for realtime access. This includes equipment purchase, spare parts and cost information; mechanical, electrical, P&I, and process drawings; initial and current configuration information along with an audit trail of the changes; maintenance records; safety procedures; MSDS sheets; etc. All of the diagnostic information reported by the smart devices above must be captured. Product analyses, blend recipes, and other production specifications are also accumulated. Objects stored in the database are not just numbers and text but also pictures, spectral analyses, links to other data sources, etc. Once the data is in the database, techniques to permit efficient retrieval of this information are a key to determining the state of the refinery. When something goes wrong in the plant, the primary objective is fixing the problem as soon as possible. It is usually necessary to gather information about the problem area – drawings, spec sheets, process conditions, maintenance history, etc. Without a comprehensive database, this data gathering often takes more time than solving the problem after all the data is assembled. Developing a common and adequate user interface for these systems is a specific challenge. Generally, the interfaces are icon based with some views keying off graphic process layouts that permit all information to be retrieved by moving a pointer to the desired piece of equipment.

Analyze

To reiterate, analysis techniques are intended to determine the best possible estimate of the current and historical state of the plant. The new developments in the measurement area plus the general increase in computer capabilities generally mean much more data is available – more than one can hope to process manually. Part of the response to this increase in data is an increase in automated analysis which takes several forms.

Data Mining –The real time data available from the refineries presents special challenges. As mentioned earlier, it is usually corrupted by noise and non-independent, i.e. both auto-correlated and cross-correlated. In addition, there is a lot of data - our ability to gather data has far outstripped our ability to analyze it. This problem is not unique to the process industries. One perhaps lesser known statistic is that the capacity of digital data storage worldwide has doubled every nine months for at least a decade, which is a rate *twice* that of Moore's law on semiconductor densities (4). However, if correlations in the data relating to production variables can be found or if precursors to failure can be identified, the potential benefits are large. Data mining is derived from traditional types of statistical analysis but is focused on processing large databases to find undetected patterns and associations. The first level tools include a number of special linear statistical techniques such as PCA and PLS (reference 9). These tools should always be the first to be used for analysis since they have well developed statistical properties that other approaches do not have. When these are not sufficient, a large number of more general tools has been developed to provide more general pattern recognition, including relations between events and determine how attributes are linked (7). Again, the major issue is the poor underlying statistical quality of process data that makes techniques useful in other fields less useful in analyzing process data.

Associated with data mining is the whole issue of visualization of large databases. Pattern recognition is significantly improved if the data can be visually displayed in a form which accentuates patterns and correlations that may exist.

Model Based Performance Monitoring –To mange something you generally have to measure it. For plant performance this normally implies using the data in some sort of model to calculate performance measures, often called KPI's (Key Performance Indicators). These performance measures are used to compare actual against plan or actual against original condition. An example is the calculation of specific energy consumption, i.e. energy consumed per unit of feed or product. To accurately assess unit operation, this calculated value has to be corrected for the current feed and product types and distribution, for the current production rate, and for the run time since the last equipment maintenance. This correction can only be done via a model of process operation. Data validation and reconciliation procedures must be used to bring the input data to the standard required by the performance analysis. With the corrected KPI's, actual operation versus plan can be accurately assessed and deviations noted.

Important questions that can then be answered include:

- What is the true maximum capacity of our equipment? Today? If it was clean? If it was new?
- What really stopped us from making our production targets last month?
- How do we accurately and consistently compare performance across all of our sites?
- How do we make sure everybody is looking at the same set of numbers?

Virtual analyzers or soft sensors are a special case of model based performance monitoring and involve the use of common process measurements (temperatures, pressures, flows, etc.) to infer a difficult to measure property using an empirical or semi-empirical model. This is, unfortunately, one of the development areas where the claims have outpaced reality by a large measure. However, progress has continued and there are a number of actual installations where real value is obtained (12). Three key limitations that are not always recognized are:

- The estimate is only good within the data region used to train the model.
- Unsteady state process conditions with a steady state model will not generally yield acceptable results since the time constants in the process will normally be different for different measurements.
- Non causal models can estimate current conditions but cannot be used to predict future behavior.

Predict

Predictive analytics

Predictive analytics is the general name for developing the best possible estimate of the future behavior of the system of interest based upon a model and an estimate of the current state. It includes a variety of techniques. In the predictive control example above, it is the model between the manipulated and controlled variables. In the maintenance example, it is the model relating deterioration in performance to potential failure. In the supply chain example, it is the demand forecasting model. Note that the control model is deterministic, i.e. there is a specific set of outputs calculated for each set of inputs; the supply chain forecast model will be statistically based – a range of outputs is calculated, and the maintenance model is event driven. These are the general types of predictions models of interest to the process industries. Most prediction model building approaches are application specific at this time. One overall key issue in model development is the necessity to use independent not dependent variables as the basis for prediction.

Decide

As mentioned earlier, a key to good decisions is efficient evaluation of the full range of potential solutions. Clearly, the improved modeling and computational capabilities has resulted in a significant improvement in the refinery staff's ability to evaluate alternatives. For example, if there was a production problem in one of a number of process units, the normal reaction in the past was to correct the problem by following the response pattern of previous similar outages. This was done not necessarily because the staff believed that it was the optimal response, but rather because the time available to respond and the available information did not support any other response. Today, it is normally possible to analyze multiple possible responses and choose one that reflects current actual demands and availabilities.

Optimization – Optimization is the general technique of determining the best set of actions within the constraints imposed that maximize or minimize the specific result desired. Most developments in refinery logistics planning, operations scheduling, and advanced control algorithms are, in reality, developments in applied constrained optimization. As optimization algorithms have become more computationally efficient and as computer processing speeds have increased, we are able to model systems in more detail with more independent variables and still complete the required optimization calculations fast enough for the answers to be useful. For advanced control the required execution time may be seconds or even milli-seconds. In scheduling, execution times of a few minutes are acceptable while for planning even an hour may be satisfactory. Naturally the models and numbers of variables will be different. Linear programming problems, which use the most computationally efficient algorithms, are now routinely able to solve problems with as many as seven million constraint equations (10). Mixed integer optimization algorithms, which have applicability to scheduling and other problems, have similarly increased capabilities. The recent history of all of these applications is the use of more complex and hopefully more realistic models that exploit the rapid advance in computing power to permit solution in a reasonable time period.

Real Time Simulation – The increased use of real time simulation as a tool for learning about complex systems such as a refinery is one of the most significant of the ongoing developments. This is most valuable in situations with very low tolerance for error or with very infrequent occurrences. Normal examples include training refinery operators to deal with emergency situations or with refinery start-up and shut-down. The key improvement obtained is a faster and safer response to these types of situations. An interesting development is the adoption of 3D virtual refinery representations for this safety training. However, the use of simulation is not limited to operator training. In fact, one of the biggest areas of increased use for this technology is in overall business simulation, particularly in the logistics area.

Expert Systems – Another technology where the hype has significantly outpaced reality has been in the use of expert system technology to assist in decision making, most particularly as operator guidance systems. Much has been proposed but few actual systems have been implemented and even fewer have stayed in use for multiple years. The modeling of actual decisions has proven to be more difficult in practice than anticipated. However, of perhaps more importance has been the difficulty in maintaining the expert systems current as situations in the refinery change. However, there remains a real need for such systems, particularly in the general area of abnormal event detection, diagnosis, and prevention. See reference 16 for recent academic work and reference 7 for some industrial comments.

Economic Benefits

There are many sources of benefits for the technologies discussed above. Smart field devices and plant digital networks are often justified on the basis of reduced capital costs versus alternate required investments and/ or reduced maintenance requirements. These can be quantified based on experience with similar installations and can be substantial. Advanced controls and real time optimization also have developed methodologies for benefit analysis (17).

However, many of the developments in “smart” refining involve more, better and faster measurements of process and equipment conditions and use of models to analyze the data. How do we estimate the value of these developments or of a database? Sometimes these economic benefits are calculated by multiplying a small potential percentage improvement in production performance times a large number such as product value and claiming that the result is plausibly the expected benefit. The causal map between the technology implementation and the improvement in production performance is not really specified. A close review of the claims shows, however, that many developments are each claiming to achieve the same improvement. The concept of diminishing returns seems absent. One source of confusion in evaluating the benefits is that only the action, the implementation, actually creates business profit or loss. How then, can we estimate the value of the improved information permitting a better decision and implementation of a superior strategy?

Assume that we have determined the "optimum" operating policy for the refinery and this generates an expected economic profit as shown in the figure below. Any estimate that we have of the current best operating policy has some uncertainty that is represented by the confidence limits around the operating line. Moreover, as we project the optimum operating policy into the future, the expected confidence limits increase and the increase is proportional to the distance into the future we project the optimum policy. This uncertainty is reflected back into the present and creates uncertainty about what the current best policy is. In other words, we now have most of the information to tell us how we should have operated last week but we don't know precisely how to operate today since it depends on events that will happen in the future.

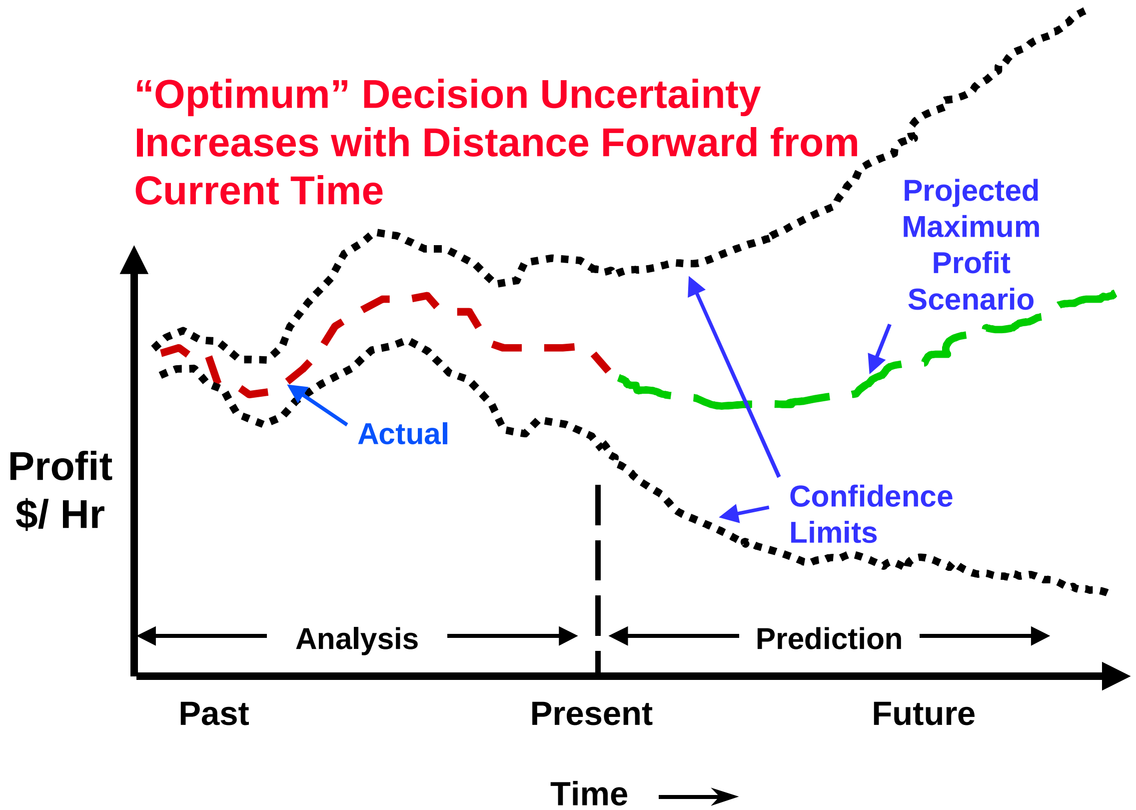

Figure 9 – Prediction versus analysis/ estimation

How can we improve the accuracy of the prediction of the future which permits us to decide better how to operate today? In general, it will be enhanced by having more accurate models, having a better estimate of the current state, and having more information about future disturbances. The decision is improved by increasing the set of feasible sequences considered, by better projection of the implication of the decisions into the future including risk factors, and by the factors mentioned earlier of better knowledge of the current state and more frequent evaluations. In simple terms, the earlier a problem is detected, the easier it is to solve.

Further, many of the technology developments can be categorized by their reduction in the expected error limits on estimates of current performance and predictions of future system behavior shown previously in Figure 9. The cumulative effect of these developments over the past thirty years has been a steady reduction in the uncertainty of the planning projections as illustrated in figure 10 below. In simple terms, we are able to predict better and hence make better decisions. In mathematical terms, this corresponds to tightening the confidence limits around the projection into the future.

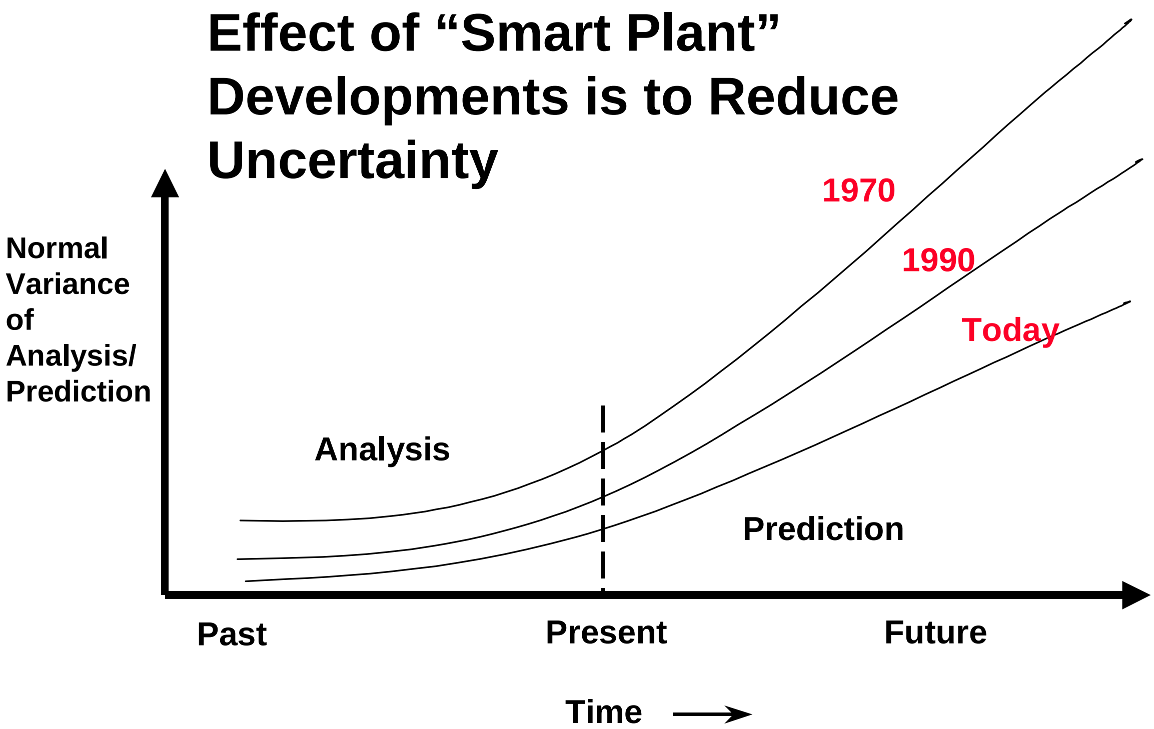

Figure 10 – Variance Evolution

Example

One of the most important process units in a refinery is the Fluid Catalytic Cracking Unit. It operates by contacting a fluidized stream of hot granular catalyst with a vaporized hydrocarbon feed in the reactor which induces a reaction to convert the feed into a variety of lower molecular, weight higher valued products. The catalyst is separated from the hydrocarbon and sent to a catalyst regenerator where the heavy reaction byproducts, "coke," are burned off the catalyst so that it can be reused. Supporting the process operation is a hydraulic circuit of catalyst as it passes through the reactor and regenerator. This hydraulic circuit generally operates with a relatively low pressure gradient with some major valves, called slide valves, controlling the flow. To ensure that hot hydrocarbons don't enter the regenerator, the pressure drop across the regenerated catalyst slide valve is monitored. An upset condition, where hydrocarbons do enter the regenerator, is called a "reversal" and is both dangerous and expensive to correct. As a result, if a low pressure drop is detected across the valve indicating that hydrocarbon might be about to flow in the wrong direction, the unit is automatically shut down. Restarting the unit after a shutdown is expensive and the lost production from the unplanned shutdown is also an economic loss. Avoiding unnecessary shutdowns while maintaining safe operation is therefore a challenge. With the circulating granular catalyst, small particles, catalyst "fines," are produced. Occasionally these fines can plug the leads to the pressure drop transmitter, simulating a low pressure drop and causing an unnecessary shutdown.

Figure 11 below shows how a modern smart transmitter with automatic detection of a plugged transfer line can be used to correct this problem. The standard deviation of the current measured signal is calculated and compared with the values when it was first installed. If there is a significant reduction in the standard deviation, it is an indication of the possibility of plugging. The alert is sent to the operator who can investigate and avoid an unnecessary shutdown without any loss of safety. One major refining group estimated that installation of this technology across their group of refinery FCCU's would save at least $1 million per year in shutdown/ startup costs and $3 million per year in lost production operating margin.

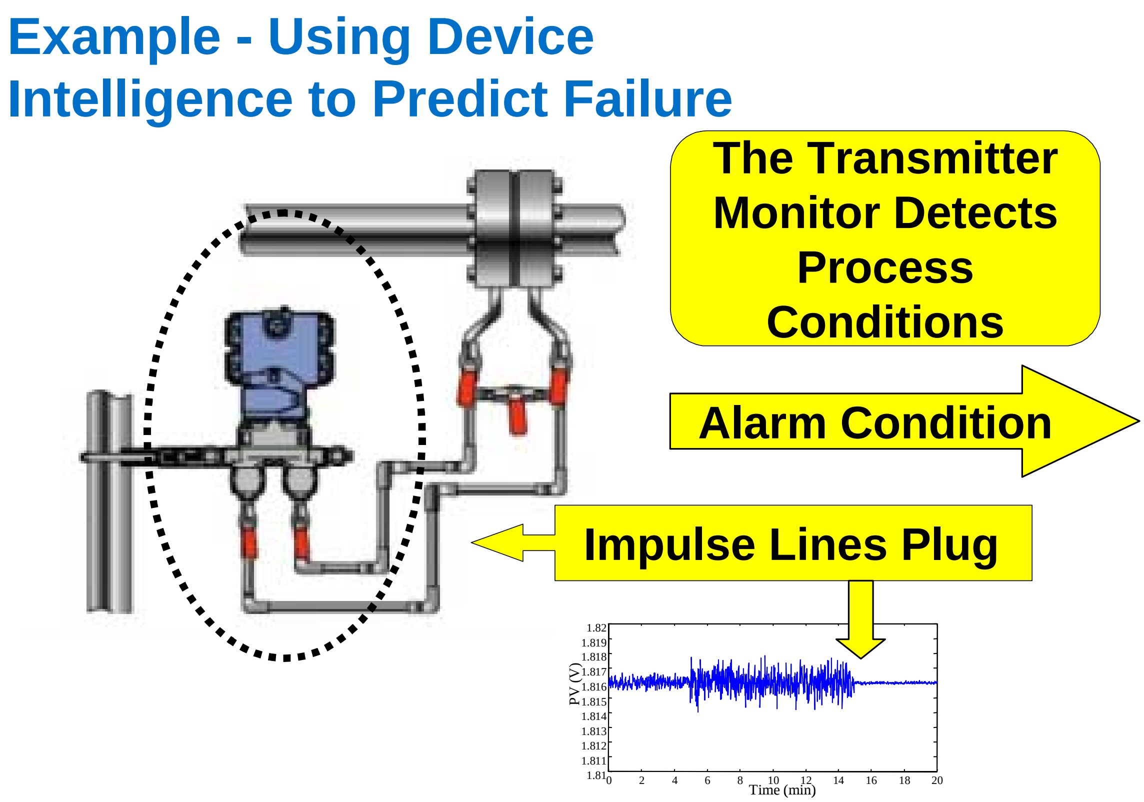

Figure 11 – Detection of Plugged Lines

Outstanding Issues

Clearly there have been many new developments in the "smart refining" arena and many successful technology adoptions. However, there are numerous practical issues that have delayed further implementation. While technology is part of the equation, it is clear that the primary issue concerns individuals and organizations. The author's experience is that the technology generally works – if not totally, at least partially. However, many new technology implementations fail on the human issues involved. Individuals and organizations are highly resistant to change. If you introduce new technology but don't change the business processes to take advantage of it, obviously the business benefits will be reduced. How to make individuals feel comfortable with the new technology and how to fit the new decision models into an organization's existing decision and power structure are the primary open questions. While these questions may seem outside the normal range of enquiry for technologists, their answers may continue to limit the rate of progress.

It is also important to retain a sense of proportion with regard to technology. Improving refining productivity and efficiency is the goal, not technology development. Quick approximate answers to the right question are more important than elegant answers to the wrong one or precise answers to the right question delivered long after the issue has passed.

Conclusion

Dramatic changes in computer and communication capabilities are occurring and will continue to have a very large impact on refinery production. The trends in manufacturing financial incentives, health, safety and environmental issues, and refinery operating demographics are driving many of the potential uses. Significant benefits can be obtained by taking advantages of these opportunities. Companies that are the quickest to take advantage of these opportunities will benefit the most.

In other industries, developments are ongoing and perhaps illustrate the path forward. The appliance division of a major manufacturer has already announced sale of refrigerators, washers, and other appliances that receive instructions and report over the web. It will not be too long until your doorbell rings and the repairman says, "I received a request from your refrigerator to come and replace the drive belt."

Can process equipment be far behind?

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