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HYDROCARBON PROCESSING®
October 2003 issue, pgs 41–50
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Creating the 'smart plant'

Before too long, your doorbell may ring and a repairman might say, 'I received a request over the Web from your refrigerator to come and replace the drive belt.' Will process equipment be far behind?

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What is meant when we refer to a "smart plant"? We are all aware of the extraordinary developments that are ongoing in the computer and communication area. Almost daily 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 process plant 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 that offer:

- More comprehensive and frequent measurements of the current state of the plant
- Increased use of models and other analytical techniques to compare what the plant is currently producing against what is expected and to understand the differences
- Earlier detection of anomalous conditions
- 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. The combination of these technologies has led to an evolutionary change in the way plants can operate. This change affects decisions and actions based primarily on the best available *prediction* of expected future conditions rather than ones principally triggered by *reactions* to what has just happened. This shift in focus is the defining characteristic of the smart plant.

A second related subject is the expected economic benefits from plant investments in these technologies. 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, many technology developments are believed to be beneficial, but how to translate this belief into realistic monetary values is not clear.

INCENTIVES FOR CHANGE

Why do we need to consider these new smart technologies for applications in plants? What plant problems are they solving that can't be solved more economically by other means? In responding to these questions, let's review three major incentive areas: financial returns; safety and environmental issues; and workforce demographics.

Financial. Operational excellence is the goal of most plants. This excellence has many components. Among these, some key objectives have a direct and significant impact on the site's financial performance. Across a wide range of HPI plants and companies, these can be summarized as:

- Produce the highest valued product mix possible
- Maximize production from existing equipment
- Maximize equipments' onstream operating (service) factor
- Continually reduce costs and pursue operational efficiencies
- Keep inventories as low as possible
- Minimize health, safety and environmental (HSE) incidents.

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

Looking at overall financial performance, the five-year average return on invested capital for the US refining industry from 1996 to 2001 has been approximately 9.5%.[1] This is at or below the cost of capital for the industry, with 2002 results generally lower. The return for the US chemical industry has been even lower for the same period at 4.5%.[2] Clearly, there are individual differences in financial performance among companies, and competitive pressures force the industry to pursue all avenues for improvement.

Where are the operational opportunities that will contribute to improved financial performance?

Energy. Energy costs remain the largest single cost component in the plants after feedstock purchases. From 1996 to 2001, they averaged approximately 8% of the value of feedstock purchases and about 30% of all nonfeedstock operating costs for the overall US refining industry.[1] Many opportunities for energy savings in the average plant remain unpursued.

Reliability. Lost production due to unscheduled shutdowns or slowdowns of plant equipment and process units remains an ongoing problem. Average losses across the process industries in potential capacity are 3% to 7%.

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

Inventory. Large inventories of feedstocks, intermediates and products are characteristic of many plants and their associated supply and distribution channels. Excessive inventory increases working capital and reduces the return on invested capital.

Smart plant components provide some of the most cost-effective investments available to achieve the operational excellence objectives listed above and improve the financial performance of process plants.

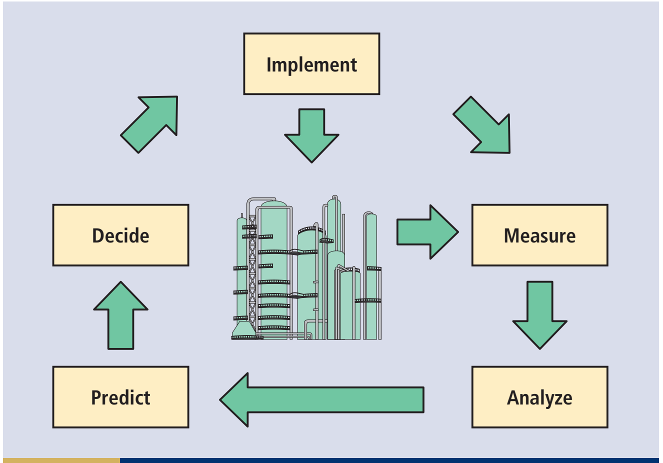

FIG. 1. Normal plant decision process follows this cycle.

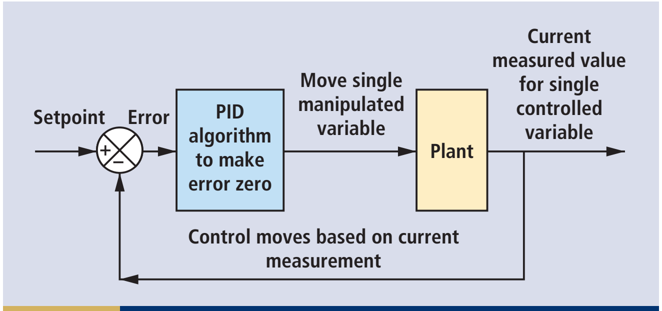

FIG. 2. Standard PID loop. Controller reacts to the current measurement.

Safety and environmental issues. The public widely views the HPI's safety and environmental performance 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.[3,4] However, reviewing the incidents and potential amelioration indicates that improved measurements and real-time analysis/detection might have prevented or at least substantially reduced the damage from a significant percentage—perhaps 25% to 50%.

Environmental emissions from plants continue to be a major problem. Although the US chemical industry 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 toxic emissions.[6] Industry along the Texas Gulf Coast—which is the world's single largest concentration of HPI sites—is under government mandates to reduce NO_x emissions a full 80% by 2007.[7] The US chemical industry has agreed to an 18% reduction in greenhouse gases from 1990 levels by 2012.[8] Meeting these goals and continuing the reduction will require many changes in plant design and operation. Improved measurements, modeling, analysis and control are key components of the required changes.

Demographics. The demographics of process plant operators in North America are changing. With industry downsizing, there was very limited hiring in the '80s and '90s. As a result, 75+% of the operators in the HPI are expected to retire in the next 10 to 15 years.[9] 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 plant measurements, modeling and analytical techniques to automate routine decision processes or at least provide the information to make the decision process more efficient.

PREDICTION VS. 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 plant (Fig. 1). We measure a condition in the plant 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; what resources are required for production including feedstocks and manpower; and when to perform maintenance on a particular equipment item. Here are the characteristics of these decision-making activities:

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

Analyze. Analysis in this context is obtaining the best possible estimate of the current performance of the system (plant) 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 plant 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 plant; 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 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. Again, analysis refers to obtaining the best possible estimate of the system's current and past state; prediction refers to obtaining the best possible projection of future behavior.

Decide. Ultimately it becomes 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.

Implement. Implementation is the actual execution of the scenario chosen. It involves all the activities required to make some change occur, most particularly, inducing individuals in the plant

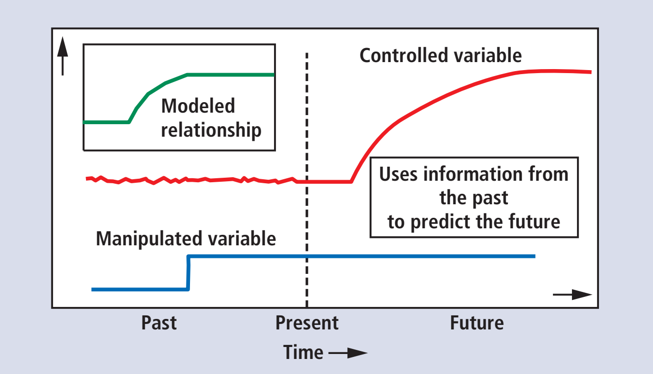

FIG. 3. Predictive control modeling. Future plant behavior is *predicted* so that action can be taken.

to perform or not perform an action. Without implementation, measurement, analysis and prediction are merely an exercise.

These decision steps are obviously not new and, in fact, have been followed in plants 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 plant, 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.

Moving toward smart operation. We can improve the overall decision process by knowing better what the plant is doing now. This implies more accurate measurements with less delay and more frequent measurements of previously difficult-to-measure conditions. Better comparison of what the plant is doing against what it is expected to do and understanding the differences leads to model-based analysis and techniques to better comprehend the information. The result is improved predicting of the effect of alternate decisions in the future. 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. Fig. 2 shows a 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 Fig. 3.

For MPCC, there is a formal mathematical model relating the response of the controlled variable to changes in the manipulated variable.[10] This then allows the control algorithm to use the history and current values of manipulated, measured disturbance 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, disturbance and manipulated variables into one controller that explicitly recognizes the interaction between

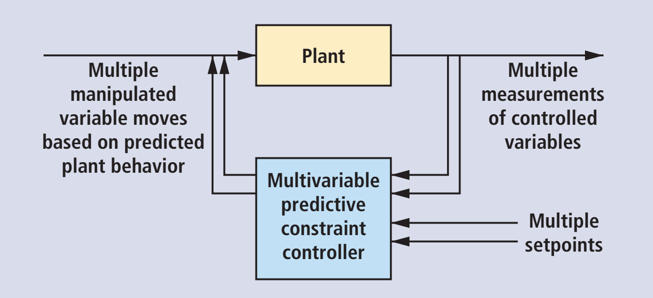

FIG. 4. Models for multiple controlled, disturbance and manipulated variables are combined into one controller.

them (Fig. 4). 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. Payout period of a few months for investments in this technology are often reported.

Predictive maintenance example. The second example concerns plant maintenance.[11] There are several approaches. 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 (Fig. 5). 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.

Predictive product demand forecast example. The staff at every plant 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. The forecast will always have uncertainty due to market fluctuations, production interruptions and transportation issues. The response is to have substantial product inventories to ensure that actual demands seldom go unmet.

In fact, many plants 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

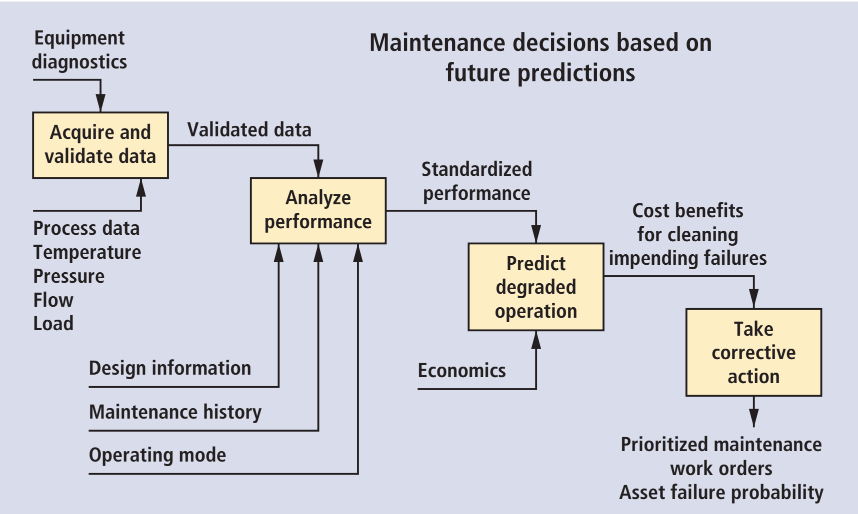

FIG. 5. Predictive maintenance. Detecting anomalies early and deciding what they imply with respect to equipment is the goal.

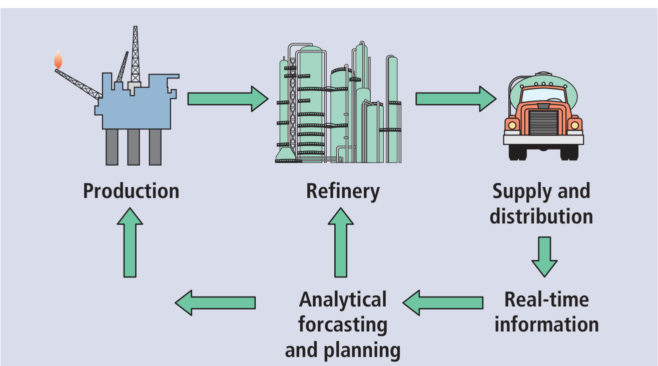

FIG. 6. Predictive product demand forecasting. Production is based on future prediction of demand.

produce more to fill the tanks back to the desired levels.

Other elements of the supply chain—production, terminals and 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 on 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 (Fig. 6) to *predict* demand and set production targets.[12] 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 implementing this technology.[13]

ENABLING TECHNOLOGIES

Dozens and perhaps even hundreds of enabling technologies permit plants to move from *reacting* to *predicting*. The following sections present those new developments having the most important impact on operations. They are referenced to their specific decision cycle position as shown in Fig. 7. Since space limits how much functionality can be covered in this article, 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 plant operation.

Measure.

Smart field devices. One of the most dramatic technology developments has been in the general area of smart field devices.[14] Increases in processor speeds, data storage and miniaturization have led to devices that are both smaller and more powerful. As microprocessors have shrunk, they have been incorporated directly into basic plant equipment. In the instrumentation area, this has included transmitters, valves and primary measurement devices 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. 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. Fig. 8 shows an example 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 needing local activation.

Advances are not limited to instrumentation. A standard electric motor that previously had no real-time measurements now has as many as 15 sensors providing temperatures, flux, run times, etc., that are available for recording and diagnosis.

Analytical procedures that could only be performed in laboratories a few years ago are now migrating to field devices. Examples include near infrared and nuclear magnetic resonance analyses.

Digital plant networks. Supporting the increases in local measurement and analytical capability has been a change from analog-based communication for field instrumentation to digital bus structures.[15, 16] This provides a corresponding increase in communication bandwidth of several orders of magnitude and permits much more diagnostic information to be moved from the smart devices to the data analysis system.

Adoption of industry standard software formats and communication protocols for these buses has facilitated interoperability among devices from multiple manufacturers. Connectivity between the plant instrumentation network, control network and plant IT network has also evolved into a reliable data transfer 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. What perhaps is less well known is the penetration of wireless communication into the plant environment. Remote sensors are being installed without wires on plant equipment where there is no need for two-way communication, and absolute reliability is not as important.

Comprehensive plant databases. Once all the data has been read from the devices and moved through the digital networks, it must be stored somewhere for analysis. Although plant databases have existed for many years, the continued evolution in their functionality has maintained their importance as the basic infrastructure or enabler for other applications. Previously the databases were primarily intended for storage of real-time process data and related calculations for historical records and trending.

Today there is a much larger set of information that must be maintained for real-time access. This includes equipment purchase specifications, spare parts and cost information; mechanical, electrical, P&I and process drawings; initial and current configuration information along with an audit trail of changes; maintenance records; safety procedures; MSDS sheets; etc. All the diagnostic information reported by the smart devices 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 are in the database, techniques to permit efficient retrieval of this information are a key to determining the state of the plant. When something goes wrong in the plant, the primary objective is fixing the problem as soon as possible. Gathering information about the problem area—drawings, spec sheets, process conditions, maintenance history—is usually necessary.

Without a comprehensive database, this data gathering often takes more time than diagnosing the problem. 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.

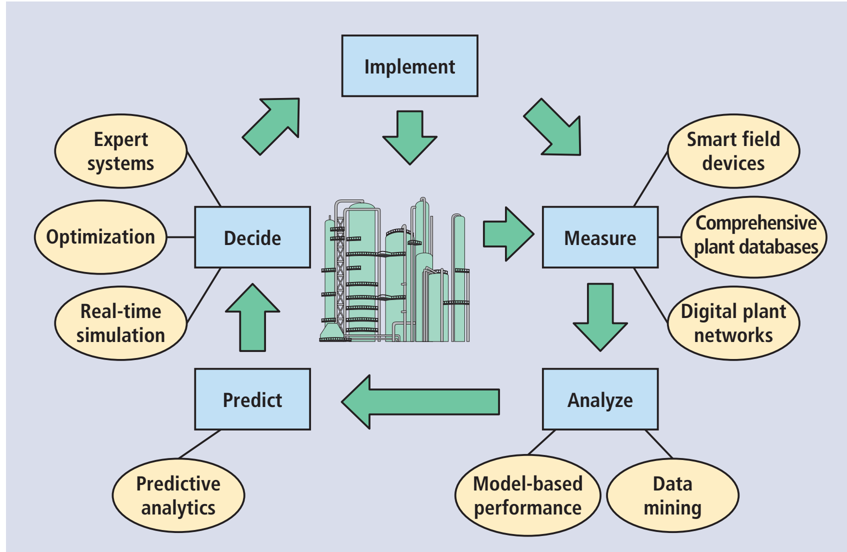

FIG. 7. Important enabling technologies and their decision-cycle positions.

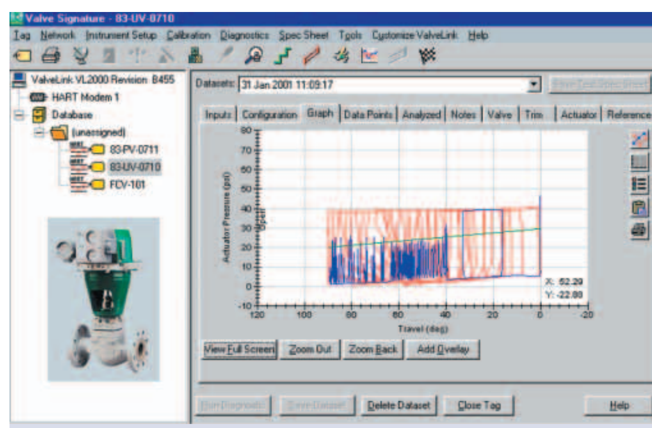

FIG. 8. Typical smart device. A malfunctioning valve reports its problem in real time.

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

Data mining. Real-time data available from the plants presents special challenges. As mentioned earlier, it is usually corrupted by noise and is non-independent, i.e., both auto-correlated and cross-correlated. In addition, there are 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.[17]

However, if correlations in 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. First-level tools include a number of special linear statistical techniques such as PCA and PLS.[18]

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 determining how attributes are linked.[17, 19] Again, the major issue is the poor underlying statistical quality of process data. This makes techniques that are 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 data can be visually displayed in a form that accentuates patterns and potential correlations.

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 key performance indicators (KPIs). These performance measures are used to compare actual against plan or actual against original condition.[20]

An example is calculating 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 performed practically 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 KPIs, 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 were clean? If it were new?

• What really stopped us from making our production targets last month?

• How do we accurately and consistently compare performance across all 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 a number of actual installations are obtaining real value.[21] Three key limitations that are not always recognized are:

▶ The estimate is only good within the data region used to train the model. To obtain reliable results, experiments must generally be run that exercise the plant over the full range of operation. Often, normal operation is over a very narrow range, and attempting to build models on this data leads to very limited predictive power.

▶ Unsteady state process conditions with a steady state model will not generally yield acceptable dynamic results since the dynamic response of the process output to changing inputs will normally be different for different measurements.

▶ Noncausal 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 a system's future behavior based on 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., a specific set of outputs is 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 prediction models of interest to the process industries. Most prediction model building approaches are application-specific at this time.

Decide. As mentioned earlier, a key to good decisions is efficiently evaluating the full range of potential solutions within the decision time available. Clearly, improved modeling and computational capabilities have resulted in a significant improvement in the plant staff's ability to evaluate alternatives.

For example, if there were a production problem in one process unit, 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 potential responses and choose one that reflects current actual demands and availabilities.

Optimization. This is the general technique for determining the best set of decisions within the constraints imposed that maximize or minimize the specific result desired. Most developments in plant 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 useful answers. For advanced control, the required execution time may be seconds or even milliseconds. 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.[22] Mixed integer optimization algorithms, which have applicability to scheduling and other problems, have similarly increased capabilities. The recent history of all 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.

Real-time simulation. The increased use of real-time simulation as a tool for learning about complex systems such as a plant is one of the most significant ongoing developments. This is most valuable in situations with very low tolerance for error or with very infrequent occurrences. Normal examples include training plant operators to deal with emergency situations or with plant startup and shutdown.

The key improvement is a faster and safer response to these types of situations. An interesting development is the adoption of 3D virtual plant 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 logistics.

Expert systems. Another technology where the hype has significantly outpaced reality has been in using 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. Modeling actual decisions has proven to be more challenging in practice than anticipated. Of perhaps more importance has been the difficulty in maintaining the expert systems current as situations in the plant change.

However, in spite of these implementation issues, there remains a real need for such systems—particularly in the general area of abnormal event detection, diagnosis and prevention—and an expectation of increased use in the future. (See reference 23 for recent academic work and reference 24 for some industrial comments.)

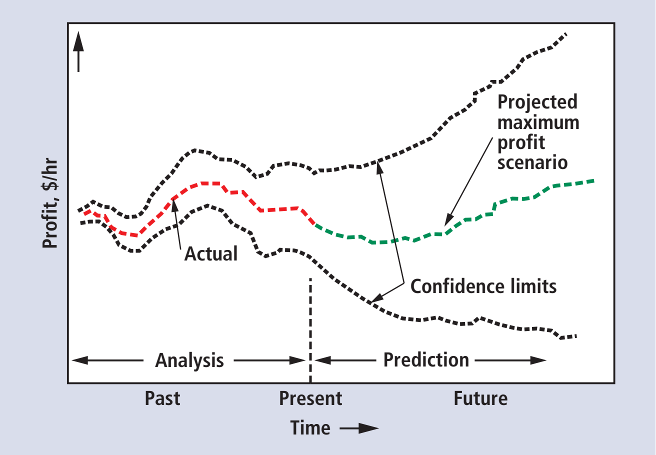

FIG. 9. Prediction versus analysis/estimation. "Optimum" decision uncertainty increases with distance forward from current time.

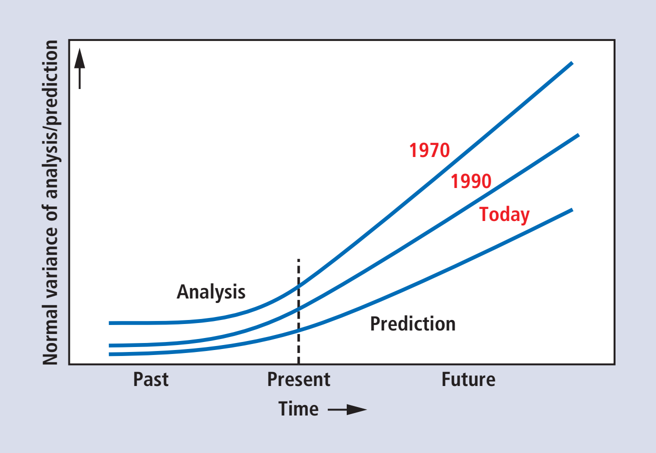

FIG. 10. Variance evolution. Effect of smart plant developments is to reduce uncertainty.

One special but important situation for expert system use is analysis of process alarms during upset conditions. As a precursor incident causes other problems in plant conditions, the number of alarms grows geometrically, and the alarm system becomes a liability rather than an asset in identifying the incident's cause. Expert systems are used to analyze the sequence and pattern of the alarms to indicate the most likely cause of the problem.[10]

ECONOMIC BENEFITS

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.[20]

However, many of the developments in a smart HPI 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 professing 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 improved information that permits a better decision and implementation of a superior strategy?

Assume that we have determined the "optimum" operating policy for the plant and this generates an expected economic profit (Fig. 9). Any estimate that we have of the current best operating policy has some uncertainty, 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.

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

Further, many 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 Fig. 9. The cumulative effect of these developments over the past 30 years has been a steady reduction in the uncertainty of the planning projections (Fig. 10). 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.

FCC unit 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. This 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, and catalyst fluidization properties are important. Poor circulation can eventually lead to an unplanned unit shutdown. Restarting the unit after such a shutdown is expensive; lost production from the unplanned shutdown is also an economic loss. Avoiding unnecessary shutdowns while maintaining safe operation is therefore a challenge.

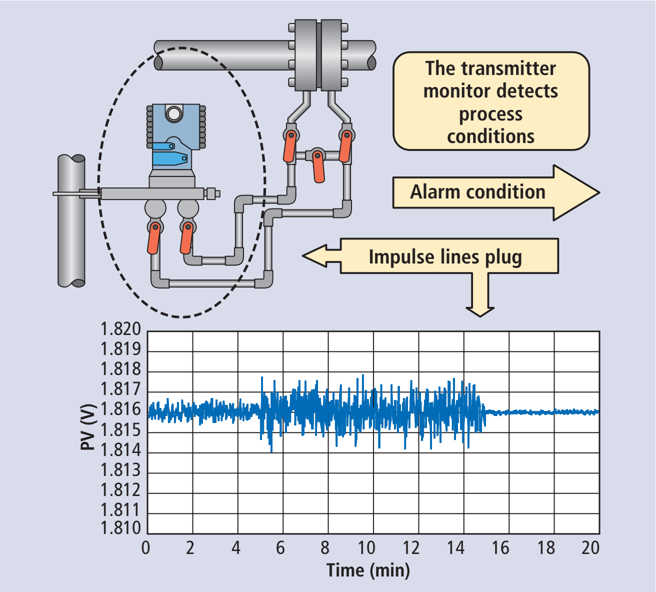

FIG. 11. Detection of plugged lines. Using device intelligence to predict failure.

Pressure measurements in the reactor circuit are used to provide early indication of circulation problems. With the circulating granular catalyst, small particles, catalyst "fines," are produced. Occasionally these fines can plug the leads to the pressure drop transmitter, preventing detection of circulation problems that might cause an unnecessary shutdown.

Fig. 11 shows how a modern smart transmitter with automatic detection of a plugged transfer line can be used to correct this problem.[25] 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 indicates 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 HPI group estimated that installation of this technology across their group of plant FCCUs would save at least $1 million/year in shutdown/startup costs and $3 million/year in lost production operating margin.

Outstanding issues. Clearly there have been many new developments in the smart HPI arena and many successful technology adoptions. However, numerous practical issues have delayed widespread adoption of these applications. While technology is part of the equation, 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 less. 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 some open questions. While these questions may seem outside the normal range of inquiry for technologists, finding appropriate answers is important to continued progress.

Also important is to retain a sense of proportion regarding technology. Improving HPI productivity and efficiency is the goal—not technology development. Technologies that provide quick approximate answers to the right question are more important than those giving elegant answers to the wrong one or precise answers to the right question delivered long after the issue has passed. **HP**

ACKNOWLEDGMENT

This article is partially based on an earlier one presented by the author at the NPRA 2003 Annual Meeting.[26]

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Form D351100X012/5KAQ/1103