Web Enabled – Real Time Business and Process Analysis to Increase Productivity in Industrial Plants.

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ABSTRACT

Intelligent systems (IS) technologies have received much attention in a wide range of process engineering applications including process operations. Due to the rapid change applying the latest technologies has become a serious challenge to both management and technical teams. Objects and components are changing the way everyone relates to their computer and networks but most feel that the rate of change will continue to increase.

All information technology systems have data and communications tools for personnel. The industrial desktop can be adapted to automate decisions, intelligently analyze large amounts of data, and learn from past experiences. This is true whether the users be operators, engineers or managers. Users can adapt their desktop according to their domain knowledge, roles, skills and responsibilities. This strategy enhances collaboration between working groups (Operations, Management, Maintenance, and Engineering). Access to data and analysis tools enables plant personnel to try new ideas, determine and track the right targets, determine and track the best patterns, and transform and store data as well as knowledge.

This paper presents a description of the data hierarchy and analysis means needed to improve process operations. Continuous improvement with an innovation loop fueled by data collection and analysis methods emerges as the best method for active decision making and collaboration.

Just a sampling of results include extended sub critical equipment availability, increased production by faster detection of process bottlenecks and operating costs reduction. Descriptions of these results in the process industries are presented.

CHALLENGES IN INSTRUMENTATION, CONTROLS AND MANAGEMENT

Process control and software developments in the process industries over the past decade have been greatly influenced by new instrumentation advances, the size/speed of microprocessors and by software developments. These developments provide opportunities for the plant personnel to effect strategies that permit them to operate the process units more profitably.

In spite of these advances, a study in the pulp and paper sector by Entech Control reports that 80% of distributed control system loops actually increase process variability as compared with manual control systems [1]. The main reasons for this increased variability were:

- 20% due to design causes
- 30% due to control tuning
- 30% related to equipment performance.

In order to maintain greater up time for any strategy, it is necessary to measure performance and continuously improve behavior [2]. The most effective tool is a continuous, real time, on-line audit called a control monitor. Every day, it will rank the loops and verify that the business needs are still valid and are being met. This list is used to adjust instrument maintenance, training of the operators and a program for management of change for the controllers. At one paper mill, they reported that monitoring plus routine action helped them increase up time of critical controls from less than 50% to over 80%.

An emerging industrial plant index called the overall process and equipment effectiveness is given by the plant availability (A) times the performance efficiency (PE) and times the rate of quality (RoQ); i.e. OPE = A x PE x RoQ where,

- A = Availability or unscheduled downtime plus scheduled downtime
- PE = Performance Efficiency (PE) or idling and minor stoppages, reduced speed of equipment

- RoQ = Rate of Quality (RoQ) or rework, yield or recovery loss.

This expression gives us the net operating time, limited by minor stoppage and speed losses. It also considers the quality defect and yield losses. The variable operating time equals the operating time minus downtime losses, speed losses and quality losses.

This same approach works with all types of equipment, not just controls. Equipment problems need to be identified and analyzed quickly; only then can they be solved. Most companies already have too much data about their equipment stored in too many locations:

- Maintenance Management systems
- Cost Systems
- Predictive Systems
- Production Systems
- Manufacturer specifications and reliability data

What is needed is an environment that simplifies integration of the data with the analysis tools. We must also prepare for the fact that with new communication, the Internet, field bus and intelligent assets (e.g. motors), there will be orders of magnitude per year increase in the amount of data available. People in the plants need tools to simplify decision-making, intelligently analyze large amount of data, and learn from their mistakes [3].

The data hierarchy framework and communication infrastructure must be restructured to improve the analytical capabilities by utilizing the software available in plant PC desktops. Most measurement problems arise from lack of easy access of data for analysis or adequate analysis tools.

The epoch development is a graphical user interface with the ability to embed for analyzing, accessing, discovering and taking actions the plethora of data from a plant. With components, this is all accomplished with reusable code that promotes continuous improvement. Proper design of this interface will make collaboration between operations, engineering and management not only possible but also necessary [4,5,6,7,8].

The Internet adds a new requirement. Many of the users that share information and analysis methods with plant personnel are located on the company Intranet and use a browser to view the plant operation and make their decisions. This means that these same components (or similar ones) must be deployable by an Internet Server into a browser – at least in a limited mode. Microsoft has introduced their DNA (Digital interNet Architecture) for Manufacturing based on the theory that the Internet is the ultimate process reengineering tool.

THE INDUSTRIAL COMPONENT DESKTOP

All business processes and the software that supports them must incorporate reusable components and promote continuous improvement. This is a key improvement to traditional plant Process Information Management Systems (PIMS). A traditional PIMS is open loop. Information is gathered into databases and disseminated as reports and on-line inquiries to all requesters; here the system's responsibilities end. This system does not promote sharing information or transforming it to knowledge **for action.** It must have a development framework to support the innovations needed for a more aggressive approach.

The new Microsoft Windows 2000 and Office 2000 software that runs on the PC in the plant, called the industrial desktop, is central to the development environment needed to support innovation. It allows the user increase his or her effectiveness by adding components to their familiar environment including video views, telephones, search algorithms or even custom components created with user level tools. This changes the individual from a fire fighter to a proactive worker. He can analyze, make discoveries about the plant and business processes and, most importantly, implement his/her findings. The user tailors his/her environment according to his/her role, skills, responsibilities, and accountability in the plant system.

Why should they do it themselves? The main reason is that all of these changes and ideas are also very difficult and expensive to transfer from one person to another and, when others do the work, much of the gratification is lost and a training issue arises. In the past, these little mini projects seldom get done. The rewards of implementing these small ideas are large and as an aggregate they become a large, high benefit change [9].

INTEGRATED DATA, ACTION, AND HUMAN INTERFACE SYSTEM STRUCTURE

A Generic Data Structure for Process Control (GDSPC) was constructed [10] to review the different tools available for process management and control in the processing industries. A schematic representation of the GDSPC is shown in Figure 1. This framework describes how the data is transformed into information and how the different levels of information for the data, action and user interface are related. The information is processed by modules at each level in timely manner. All information is saved for historical analysis.

The data processing hierarchy is composed of:

The data acquisition subsystem,
The data validation subsystem,
The data classification and analysis subsystem,
The data verification and estimation subsystem,
The plant data management subsystem and,
The plant data optimization subsystem.

The first four levels of the data processing are real time tasks. They need to be processed on a time class demand. The plant data management and plant data optimization processing are to be performed depending upon operation planning and economic evaluation time frames (transactions).

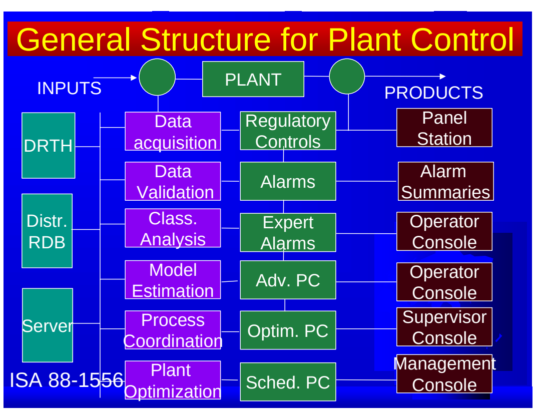


Fig. 1. A modular approach to manage data, actions and analysis.

The Data Acquisition Subsystem

The first layer is the acquisition of the measurable process variables from transducers and output of variables to the actuators, and the digital input and output. At this level, instrument diagnosis can be implemented. Even with the use of smart transmitter, these cannot detect, not correct for, a drift or span error until the transmitter output has been compared with known signals or values at operating conditions [11].

The Data Validation Subsystem

The data validation step can be implemented by several methods. The traditional method is to check for validity by using a known relation that must hold true. Each process measurement and resultant calculations are compared against high and low limits as well as a maximum rate of change. Depending on the type of process a voting technique can be used when the measurement is so critical that two sensors can be economically justified. The results of the data verification step are posted to an alarm summary and/or to a data logger.

The Data Classification and Analysis Subsystem

The classification and analysis of the validated process data divides the process into several modes or operational status. This classification is facilitated by the incorporation of common-sense rules dictated by expert operators and process engineers. These triggers are calculated indexes, which define a state of the process unit or equipment. It is used to define a production, quality, cost, environmental or equipment status.

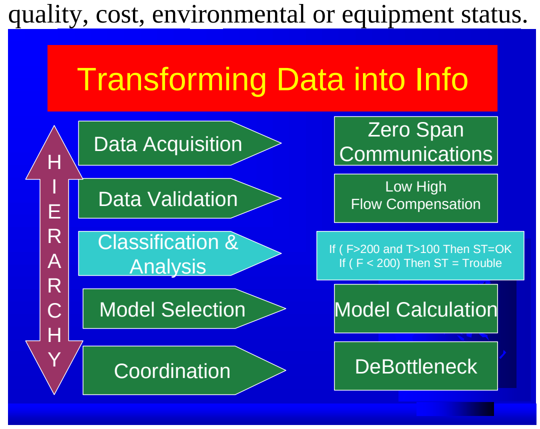


Fig. 2. Plant data hierarchy example.

The trigger indicator (Active Tag) is used in real-time applications or to enhance the historical data extraction for calculation of mass balances, total operating hours under certain conditions, to select the type of model to use in inferential or economic functions.

The utilization of several timeframes of a data point such as data average, moving average, minimum, maximum, standard deviation and rate of change can be utilized to classify the faults or process status. The history of process values, events and alarms is usually available but never automated. These time-series of variables are available to extract pattern features to check for deviations from normality. The node type system is used to minimize the computer processing time. In this generic data action hierarchy a human equivalent metaphor is used. For example, if the communications is broken, or if the sensor is in troubles, or if the process is in a certain status, special detailed detection is set for further data processing.

Communication status node - The first item to check is the communication link between the control subsystems. Any missing process information required by the unit advisor should be detected and acknowledged as soon as possible. The detection of on-line analyzer malfunction should be incorporated under this data analysis subsystem.

Equipment monitoring and diagnosis (Trouble node) - The data subsystem should recognize the unit equipment sensors and actuator limitations and the safety restrictions. The data trouble subsystem should act as an advisor to ensure that the process-state does not violate such limits. The history generated by these types of points is used for predictive maintenance of instruments and sub-critical equipment. The technical methods for detecting and responding to failures are documented in the literature [12, 13], Diagnostics and Reliability Based Maintenance, http://www.rosemount.com/products/ams/rb-maint.htm (Internet), May 8, 1998. In addition, simple checks can be implemented such as power draught, oil pressure, vibration and amperage in rotating equipment, pump efficiency estimation, rate of change to detect leaks in fluid lines, etc.

Process operational status node - This data subsystem helps the operator by advising him of tasks that require manual intervention. The operator will only take care of the process units, which require special attention and try to solve plant bottlenecks. Data classification and analysis should prevent over controlling the process units. In this manner, the operator will be able to have a global vision of the situation and be prepared to solve real troubles. The availability of correct action response can have a large effect on plant performance.

Control advisor node - Depending on the type of economic objective there are several forms of control available for a process unit. For example, when a preprocessing part of the plant is down, the next sub-process could slowdown and change from a maximizing throughput objective to an improved product quality objective. This control strategy will be set in time following a guided procedure with proper interlocks on the control stations. Example: A slow varying system requires the analysis of historical data acquired over several hours.

The Data Verification and Estimation Subsystem

After data has been classified and a process operational status identified, further process inference can be obtained by using estimation of unmeasured variables for the implementation of soft sensor analyzers.

If the process is considered to be at a steady state a form of data reconciliation can be used. A mass balance closure adjustment can be used. The adjustments are based on a weighted least square fit subjected to the mass flow rate and composition mass balance techniques.

Other techniques use multi linear regression (MLR) techniques, projection of latent structure (PLS) or neural network modeling to infer the property from other variables. Sometimes stochastic features are added to include the plant noise. In some instances thermodynamic models and process measurements are used to infer properties. (End-point, freeze-point, flash point, and cloud point type calculations in fractionation systems).

A state variable approach can also be used to provide optimal estimates using Kalman filtering techniques [14]. In this method, the estimates are calculated by proper weighting of information provided by a process model and the measured variables. The weighting is based on statistical properties of the process and the available measurements. These techniques add a great value to current instrumentation with a minor investment in proven software for an existing distributed control system. Estimation techniques can be used very effectively when an on-line analyzer is not justifiable or reliable. The process visibility obtained by these methods allows better design of the process controllers and plant accounting and planning systems.

The Plant Data Management Subsystem. Once the missing data for the process units is acquired or constructed for inexpensive process data, the coordination of these units is possible. At this point, each process unit is controlled in a sub-optimal fashion if other unit interactions (product variability and inventories) are not taken into consideration. To provide for a sound operation the coordination of the process units needs to be incorporated. Items such as production rates, maintenance schedules, energy considerations, capacity limitations, demand and process constraints are set according to plant economic objectives.

The presentation of the plant data in adequate reports improves for downstream decision making. Plant, sections or units material and energy balance reports, calculation of global performance indexes as well as raw material and products quality and inventories, all can be facilitated by easy access to real time process data and plant data base system. The availability of special functions (totals, averages, searches, statistical analysis, time calculations, etc.) increases the efficiency of data consolidation and presentation.

Traditionally, supervisors set the operating conditions and communicate these targets to their operators. The industrial desktop enables to close the gap between operations and management. The data coordination subsystem defines the level of collaboration between the operations and maintenance functions. The implementation of workflows avoids chasing of conditions to meet the targets which sometimes might result in instability and costly product losses.

The Plant Data Optimization Subsystem. At the top of the hierarchy the data obtained is processed to evaluate the global profitability of the operation. The validated data and calculated technical indexes should be combined with operational costs and production indexes. The data forecast resulting from consideration of the current market conditions and plant availability are fed to the planning functions to set the maximum profitability. At this level, the development at the industrial desktop towards planning, act and measure are the key for achieving high results. The integration of process efficiency and equipment operability functions with unit availability status and anticipated scheduling commitments are defined. The data validation, classification and verification are vital since the optimum will depend on having accurate data and a validated process model.

The data is used to develop a recommended unit action plan for plant operations to balance limited resources, operating cost variances, estimated repair costs, utility costs, and projected revenue opportunities. At this level the information is feed into enterprise information systems.

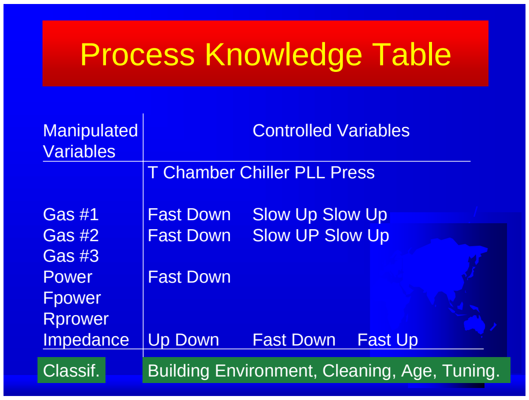
PROCESS ANALYSIS AND DEVELOPMENT

Emerging new data analysis technologies are becoming available to expand the detection of cause and effects of multivariate systems. These tools facilitate analysis of multivariate systems such principal component analysis, PCA and Projection of Latent Structures (PLS). These powerful techniques allow users to monitor the statistical state of many variables from a few graphical views of the principal components or latent variables [20,21,22,23,24].

When processes are subject to large unknown disturbances, the alternative of applying operator mimic as been successfully used [15,2]. A degree of imprecision can be assigned to the generated procedures, which can be exercised under a real time environment. The use of time derived variables are highlighted in the development of a Process Control Matrix and the Construction of Historical based decision table (Figures 3 and 4).

The concept of approximate reasoning is used to model the process in question [16,17, 18]. This method of visualizing and condensing information from many process variables into simplified tables capturing knowledge out of data. It also presents the quality indicators against the process data.

The representation of the cause and effect of the process model is captured using a linguistic approach. The tables are generated using empirical or deterministic models. The key is that the model has a degree of fuzziness.



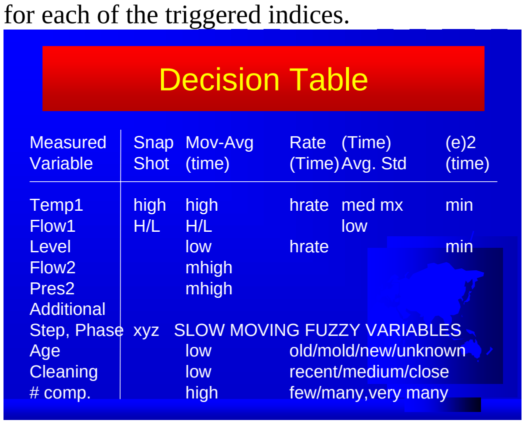
Process Knowledge Table

Manipulated Variables	Controlled Variables		
	T Chamber Chiller PLL Press		
Gas #1	Fast Down	Slow Up	Slow Up
Gas #2	Fast Down	Slow UP	Slow Up
Gas #3			
Power	Fast Down		
Fpower			
Rprower			
Impedance	Up Down	Fast Down	Fast Up
Classif.	Building Environment, Cleaning, Age, Tuning.		

Fig. 3. Process knowledge table.

The process knowledge table describes the effect of control variables by manipulated variables subjected to the observed variables (Figure 3). It uses a fuzzy description of the response or historical pattern. The observed variables are usually slow moving variables which define the operating conditions such as the age of a well, age of the catalyst, pump characteristics, equipment wear, or the cleanness of the reactor.

The decision knowledge table also uses linguistic approximations and developed using time-derived variables (Figure 4). These auxiliary variables are used to develop the trigger points necessary to develop the operating condition status indices. The use of the historical data is stressed to define at all times the process pattern. The subset of data used to develop the soft limits can be obtained by classification of the variables for each of the triggered indices.



Decision Table

Measured Variable	Snap Shot	Mov-Avg (time)	Rate (Time)	(Time) Avg. Std	(e)2 (time)
Temp1	high	high	hrate	med mx	min
Flow1	H/L	H/L		low	
Level		low	hrate		min
Flow2		mhigh			
Pres2		mhigh			
Additional					
Step, Phase	xyz	SLOW MOVING FUZZY VARIABLES			
Age		low	old/mold/new/unknown		
Cleaning		low	recent/medium/close		
# comp.		high	few/many,very many		

Fig. 4. Process operating condition decision table.

Figures 3 and 4 show an example of a process knowledge table generated using the presented approach. The trigger point calculation are implemented either for real-time execution at the server level for on-line diagnosis or at the client for process data analysis and development of the trigger actions.

PROCESS TROUBLESHOOTING EXAMPLES

A good example is the Microsoft interactive software agent (Figure 5.). Basically, the agent provides a conversational user interface, which normally is employed to enhance, rather than replace, the usual Windows graphical interface. The activation of this agent can be set in the real time environment by a real time event called change event. As such, you can have this Agent explaining why key process indices have gone outside a certain range. The activation of the agent can use the described method for defining the trigger indicator based on sharp or fuzzy rules. The Agents (Genie, Merlin and Robbie) have a palette of animations, a synthesized voice, the ability to synchronize its movements with recorded voices, and the ability to respond to mouse clicks, internal events and voice commands. You can implement Agents through either a COM interface or an ActiveX control. You can start from an example and tailor it to your needs [19].

In this example the client software container has a VBA script enables to automate the genie Active X component based on a real time change event generated at the desktop.

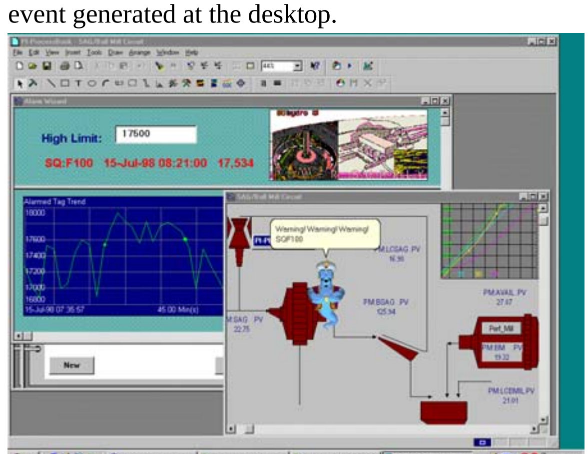


Fig. 5. Microsoft Agent triggered by a change value event at the Industrial Desktop.

Spreadsheet Real Time Filtered Data Extraction and Exception Reporting

Instead of searching, retyping information into the spreadsheet, Figure 6 shows a spreadsheet is set to run every morning a 8 AM and get the data and exceptions for a metallurgical temperature of a reactor. Every morning, this filtering is executed prior to arriving to the office. (Note: This exercise can be scheduled at any desired time, every minute, hour, shift, etc.). At the same time, a correlation between the dependent and independent variables is performed to check the relationship between the independent variables. If these correlation coefficients have changes, the relationship is no longer valid and adaptation of the model is required.

The extraction data requires special filtering to obtain a subset of data. These methods are build as special methods to reconstruct the most appropriate time series. Usually, quality, process equipment, environmental data are collected at different scan times that the process data. Special methods should be available to reconstruct the data set for the scan times available of the key indicators. It is important to recognize that once the spreadsheet template is built, it can be re-used for other time’s interval. As such, it can be used every time (minute, hour, shift, day) for fault diagnosis.

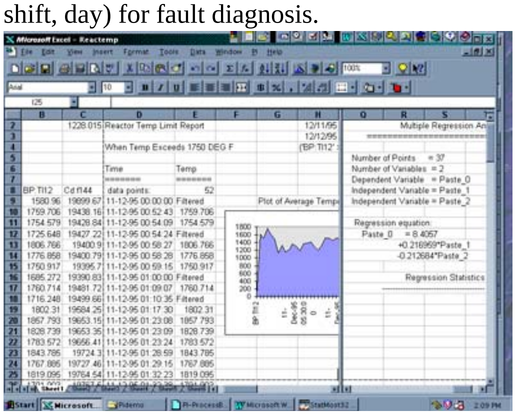


Fig. 6. Automated exception report and process data correlation.

The information collected using the same spreadsheet can be analyzed by multivariate methods. As such multiple quality variables and used in conjunction with process data to provide an assessment of the plant behavior.

Multivariate statistical methods are very effective at extracting hidden information in problems with multiple correlated variables [20,21,22,23].

In addition, having access to the process data at the desktop enables the users to develop neurofuzzy applications [25]. This reference describes how to add a fuzzy tool Add-ins to Excel to generate rules to develop model for analysis of data. As such, the same spreadsheet with the process data subset can be used to transform data into knowledge for faster and better business decision making.

The workstation real-time environment described above can be enhanced by the availability of mathematical objects available in the market. These software packages are usually data intensive and they require the data classification methods discussed earlier.

Although the function here is quite simple, the underlying infrastructure necessary to make this happen is not. Effectively, the user can customize or manipulate PI objects in any manner desired. For example, if a user has a database of start-ups and tests, he/she could develop an application that automatically sets the time on the displays back to that time frame. This database could reside in the Batch tracking module or some external database.

Exemption Reporting in Batch Processes. Figure 7 shows data analysis tools to detecte if a batch in progress meet the specifications of the golden batch. Such technique permits batch analysis without the need to wait for further processing or quality control. A subset of good batches is used to obtain representative high and low pattern limits for each of the phases in the batch process. Once, it is shown that it a key variable has violated a certain amount of times the acceptable envelope, the product can be discarded or recycled.

CONCLUSIONS

A robust environment at the industrial desktop provides with real time, historical process/equipment information and business information for all functions in the process industries. This environment enable users to build, construct and maintain their views of the plant for simplified performance monitoring, process and equipment troubleshooting, continuous improvement and innovation.

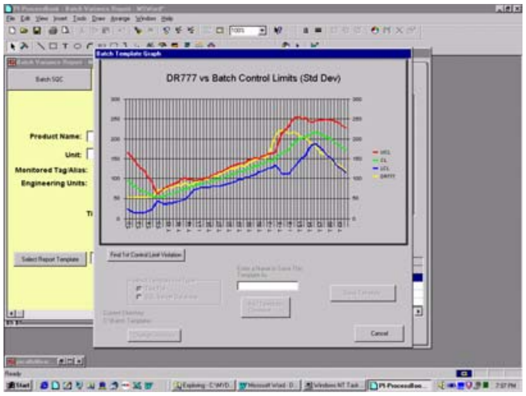


Fig. 7. A graphical representation of the batch exemptions compared to the golden batch pattern.

In general the results can be summarized as follows:

- Improved quality and speed of plant monitoring and diagnosis
- Optimizing plant efficiency performance (by continuous improvement and innovations)
- Condition based maintenance
- Improved production and regulatory information
- Consistent and comparable information across the enterprise (benchmarking).

These technologies are available today to rethink plant operations and to increase the performance of existent production systems. The key to re-engineering is linking people, business processes, strategies and the best enabling technologies. Many benefits are available that do not require disruptive re-engineering

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