Next Generation Pump Systems Enable New Opportunities for Asset Management and Economic Optimization

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The benefits of machinery monitoring and condition-based maintenance may be significantly enhanced by integrating real-time diagnostics & prognostics techniques within the framework of an automatic control system. The integration of prognostics with control provides unique opportunities for dynamic compensating control and ultimately for managing and optimizing asset utilization.

Narrative Biography

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Since 1972, Dr. Discenzo has been working on advanced computer technology applications. He has been with Rockwell, for 21 years and is currently the Manager, Diagnostics and Sensors in Rockwell's Advanced Technology Laboratory in Cleveland Ohio. These activities are targeted at developing novel sensors, diagnostics, and control capabilities. Fred is also an instructor at Case Western Reserve University and periodically conducts workshops and talks on various aspects of Technology Development. He received a BA and BS degree in Mathematics from The Ohio State University, an MS in Polymer Physics from The University of Akron, and a Ph.D. in Systems and Control from Case Western Reserve University.

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ABSTRACT

There is growing interest in cost-effective techniques that can detect the earliest stage of degradation or malfunction and predict machinery failure. New diagnostic and prognostic techniques may be effectively coupled with novel control techniques in the context of an intelligent motor-pump-control system. An integrated intelligent system is described for pumping applications that can sense the operating condition and health of the components of a hydraulic system and automatically change the operation of the motor-pump system. The change in control is goal-directed whereby the prescribed operating change is intended to achieve previously defined operating goals or performance objectives.

The operation of an intelligent motor-pump system in an integrated, coordinated manner can achieve unprecedented and important capabilities for protecting critical processes, process equipment, operations personnel, and the environment. This system also provides a basis for dynamic optimization of critical operating and financial objectives such as longest MTBF, lowest life-cycle cost, or lowest cost per gallon pumped. Future intelligent systems will provide the basis for next generation CBM systems, future distributed intelligent systems, and autonomous, agent-based systems.

INTRODUCTION

Reliable and efficient operation of machinery remains a critical priority for many commercial and industrial organizations. Focused efforts over the last decade have been very effective in reducing manufacturing material, scrap, labor, and inventory / work-in-process costs. Various methodologies and frameworks have been established that are directed at improving anufacturing financial performance with process changes and metrics. Maintenance remains one of the single largest controllable expenditures in many manufacturing operations (Anderson, 1996). The impact of applying new maintenance techniques with predictive maintenance can be significant. For example, a cement plant recently was able to add $5 million / year to the bottom line by applying these methods (Schulz, 2001).

An effective condition-based maintenance (CBM) program can significantly reduce maintenance and repair costs. There is growing interest in quantifying the benefits of a CBM program in terms of hard dollar savings and business opportunity provided. The potential saving are far reaching and go beyond reducing maintenance, repair, and operating (MRO) costs. In addition to operating cost savings, the useful life of machinery may be significantly extended thereby deferring capital expenditures.

There are compelling business drivers that often make cost-effective machinery reliability not only economically sound, but also a business imperative. These recent business drivers include greater concern for protecting the environment, ultimate concern for worker safety, connected (e.g. virtual) organizations, make-to-order operating strategies, and competitive time-based performance with greater scrutiny and expectations in a rapidly expanding e-business world.

We see significant opportunity by closely coupling machinery health (e.g. diagnostics) and anticipated health (e.g. prognostics) information with real-time automatic control. In particular, the closed-loop performance of a system under feedback control provides an indication of the responsiveness, and indirectly, the health of the process equipment and process operation. More importantly, it is possible to change how the system is controlled, within certain limits, to alter the rate of machinery degradation or stress.

Using real-time diagnostic and prognostic information we may alter the future state of the machinery. Given a current operating state for both the machinery and the process we can drive the system to achieve a prescribed operating state at a particular time in the future. This future operating state can be specified to be an improved state than would occur if we did not alter the control based on machinery health information. Furthermore, the future state we achieve is chosen to be optimal in some sense such as machinery operating cost, machinery lifetime, or mean time before failure. The prescribed operating state of a particular machine may be sub-optimal however, as part of an overall system, the system-wide operating state may be optimal with regard to energy cost, revenue generation, or asset utilization.

The techniques described here go beyond conventional closed-loop feedback control and optimal control methods. Established control techniques are extended with dynamic machinery diagnostics and prognostics information. An assessment of the current machinery health (e.g. state estimation) and state trajectory is used to define a control sequence that will meet process requirements while maximizing machinery lifetime or optimizing asset utilization. This approach integrates performance, maintenance, and business objectives in an optimum manner while avoiding unexpected or catastrophic equipment failures.

We present a summary of relevant diagnostic and prognostic developments and the relevant embedded controls used for automation machinery. The techniques we present are applicable to a wide range of automation systems including compressors, fans, conveyors, motion control, mixers, package handling, and web processing. A pumping system was selected to demonstrate these concepts since these systems are prevalent in industry and basic system operation is generally well-known and can be readily described and tested in the lab. We present this pumping system controlled with a variable frequency drive as an example of diagnostics and prognostics with compensating and optimizing control.

The capability presented below provides a basis for protection of equipment, facilities, and personnel and from an enterprise standpoint establishes a new, fundamental capability for enterprise asset optimization systems (EAO) of the future.

BACKGROUND

Commercially, pumping systems are very important since many industrial motors are employed in pumping applications. Some estimate perhaps 40% of industrial motors are used in pumping applications, and together, pumps and fans may represent perhaps 70% of global industrial motor applications (Nelson, 2001). Lastly, the operating costs of motor-pump systems can be very high and as much as 50% of the total plant energy costs in some cases (Frenning, et al., 2001).

The integration of diagnostics, prognostics, and control effectively leverages off recent developments in condition-based maintenance support systems and enables new opportunities for intelligent control. An integrated, intelligent control method provides a method to identify potential desirable and undesirable machinery states and then to control the system to avoid the problematic states. Examples of undesirable operating states to be avoided include excessive vibration such as occurs at resonant frequencies, motor winding failure, and pump cavitation. In addition to avoiding these undesirable operating states or delaying the time to failure for a critical component, we may further enhance the control specification with other process and business information. This enhanced control scheme may then perform real-time optimum control (e.g. dynamic optimization).

The capability for enhanced machinery control and asset optimization is based on the unique integration of established methods for diagnostics, prognostics, control, and optimization. These may be combined in a staged approach to provide incremental, graduated degrees of capability and benefit as shown in Figure 1, Stages of System Integration. Subsequent sections of this paper describe the relevant foundational elements of diagnostics, prognostics, advanced control, and optimization. These techniques are brought together in a simple, demonstration case study.

DIAGNOSTICS AND CONTROL

Diagnostics

There are many established data acquisition and analysis techniques for machinery diagnostics. Some of these methods require the machine, such as a motor, to be off-line and disconnected from power. Other techniques utilize portable mobile instruments to acquire data with subsequent, batch-mode data interpretation. Our focus has been on algorithms and sensors that provide on-line, continuous monitoring and diagnosis of rotating machinery. This real-time health information is intended to identify degraded equipment, equipment that may soon fail, or unusual operating conditions that may accelerate machinery deterioration and hasten machinery failure.

There is growing interest in detecting the initial stage of defect formation and to estimate the remaining useful life and eventual failure mode of machines. Early indication of the inception of a fault coupled with models describing the expected degradation rate or progression rate of the defect will provide a first-level approximation of the residual lifetime of the machinery. Both statistical and model-based techniques show promise in extending the accuracy and viability of prognostics methods. For example, there exists rules-of thumb which describe the reduction of insulation life based on the winding temperature rise and typical L10 bearing life models provide a rough indication of the expected life of bearing components. Stochastic crack growth models may be used to consider the effect of vibration, temperature gradients, and pressures to determine crack growth life and eventual mechanical failure. Prognostics leading to future state estimation are particularly important for future pumping systems. By coupling future state estimates with closed-loop control we can direct the system to achieve (or avoid) future operating conditions.

Typical instrumentation for on-line rotating machinery diagnostics includes temperature sensors, vibration sensors, proximity probes, IR imaging, current sensors for electrical faults, and acoustic sensors. Operating conditions such as bearing faults, cavitation, blockage, and multi-phase flow have been established using pressure transducers, acoustic sensors, accelerometers, and in some cases just motor current (Koivula, 2000)(Discenzo, 2000b). Recent work is focused on extending the capabilities of motor current signature analysis (MCSA) techniques to non-electrical components. For example, the ability to diagnose bearing faults, gear faults, and pump faults such as cavitation and impeller failure are important new capabilities (Vetcha, 1998). Diagnostics based on motor current do not require that sensors be located on remote equipment thereby avoiding difficulties associated with environmental protection, possible hazardous locations, sensor wiring costs, and the need to transmit sensor signals long distances. In fact, current signature diagnostics may be done remote from the installed equipment and in the controlled environment of a motor control center. The information provided by established instrumentation and analytical methods provides a basis for defining possible future operating states of the controlled system.

Virtually all of the diagnostic methods employed for determining the condition of equipment while operating are employed as passive monitoring techniques. Unique and important capabilities exist with the integration of real-time monitoring and health assessment with established control techniques.

Control

Developments continue to improve the performance of controlled systems. The scope of these developments include self-tuning and adaptive control methods, other non-linear control techniques such as model-reference control, and optimizing control methods. These techniques have significantly improved the commissioning time and robustness of complex coupled processes and processes with instabilities and non-linearities such as backlash. Dynamic optimization methods have been applied for many years to improve the yield of certain continuous process operations.

In spite of the large base of established, readily available control algorithms and motor control hardware, pumps are typically used in an "across-the-line", stop-start mode. The control of the pumping process is done by cycling the motor connected to the pump on or off as desired and regulating the amount of flow by flow control valves and diverters. Perhaps 90% of the pumps in industry are operated this way. Very few motor-drive pumps utilize a drive to control the motor-pump.

In the British industry, around 40% of the total industrial electricity usage is used to power ac motors for fan and pump applications and most of these are driven directly from line power at constant speed (DPA, 2000). A substantial amount of energy is wasted since at the time of purchase, systems are typically oversized as a contingency and motor selection is based on rounding up to the next standard motor size. Perhaps as much as 50% of the energy consumed is wasted by oversized systems controlled with constant speed operation.

Similar energy savings have been demonstrated in laboratory tests conducted by the authors. We have utilized a pump loop consisting of a 2 hp, 3-phase, 460v, ac induction motor coupled to a centrifugal pump (Figure 2, Intelligent Pump Controller Demonstration System). The motor can be controlled either directly from line power or controlled with a variable speed drive. A Yokogawa power meter was used to measure total input power (kW) to the system. The results of our tests are shown in Table I and substantiate the estimate of 50 percent energy savings when operating at reduced flow. We achieved a 53 percent energy savings while operating at 45 gpm and a 10 percent energy penalty at full flow when operating at 75 gpm, maximum flow. The 10 percent energy penalty is due to losses in the inverter. A variable speed drive is typically a very efficient device and any losses due to switching and processing are quickly more than compensated by losses in un-necessary flow or head pressure at reduced flow.

Pumping applications that require operation at various prescribed head pressures, liquid levels, flow rates, or torque / speed values may be effectively controlled with a variable speed motor drive. The benefits of using a variable speed motor controller for pump applications are well established, particularly for pumps that do not operate at full rated flow all the time. In fact, the variable speed drive we used for our testing has a user-selectable factory setting optimized for fan and pump applications (GV3000, 1995) although we chose not to use these optimized settings for the energy savings reported here.

The scope of benefits beyond energy savings include improved machinery reliability, reduced component wear, and the potential elimination of various components to such as diverters and valves and components for protection such from over-current or under-current operation.

Pumps which typically operate at or near the best efficiency point and at constant speed will not realize the energy savings as we have demonstrated in Table I. Process conditions that require pump operation at different flow rates or pressures (or are permitted to vary operation within process constraints) are candidates to realize substantial energy savings such as we have shown. If maximum throughput is only needed infrequently, it may be beneficial to specify the hydraulic system and associated control to optimize performance over the complete span of operating modes based on the time spent in each mode. It will be necessary in this case to specify the duration of time the hydraulic system is operating at various rating levels. For example, Figure 3 shows an example pump system operating levels over time. The few, rare excursions at maximum flow result in hydraulic losses and energy losses during most of the operating time at lower flow rates. Integrating the losses under the peak efficiency curve provides an estimate of the aggregate losses (and saving opportunity) for a target pump applications. Aggregate pump level usage information is represented in a very concise manner by Frenning (Frenning, et al., 2001???) in a duration diagram. This diagram shows the number of hours per year needed at various flow rates are needed and provides a means to evaluate potential performance and energy benefits through up-front system design and control specification.

Beyond these established benefits, there are important new benefits by integrating diagnostics and prognostics information with established automatic motor control methods.

Integrated Diagnostics and Control

Diagnostic information that provides equipment and process health assessment is rarely integrated with industrial control, even though both systems may be part of the same machine and both systems may be running in parallel.

At a trivial level, some may consider an automatic disconnect based on an excessively high current or temperature to be integrated diagnostics (i.e. something is wrong) and control (i.e. automatic contact closure). For the purpose of establishing an intelligent system for pump applications as described above, we do not consider such machinery protection with bang-bang, on-off control to be integrated diagnostics and control.

The diagnostic information we require is information regarding the condition of system components or operating conditions that will affect the rate of wear and hasten failure of critical system elements. For example, information that identifies the level of degradation of a bearing element, the degree of insulation capability lost, the amount of time motor windings were operated at elevated temperature or that cavitation is occurring is useful diagnostic information. This information can be combined to automatically alter the prescribed control action, within allowable limits, to maintain useful operation and potentially reduce the stress and degradation rate of weakened components. The ultimate effect is to defer, under controlled conditions, eventual machinery failure. For example, the use of machinery performance monitoring coupled with control has provided increased reliability / availability and reduced noise and vibration coupled with a decrease in emissions and improved fuel efficiency for a two-stage compressor (Harrold, 1999).

Feedback control for pumping applications will often have one or more process variables such as flow rate, head pressure, or liquid level sensed by a transducer and converted to a digital signal. This digitized signal is then input to a control computer where the sensed digitized value is compared with the desired, setpoint value. Any discrepancy between the sampled value and the setpoint value will result in a change in the control action to the motor-pump system. The change to the motor-pump system may be a new commanded valve position for a motor-operated valve or a new commanded setpoint speed for a variable speed motor application.

Feedback control systems as described above are termed error-nulling processes. We may represent the feedback controlled pumping system as a lumped parameter linear system. The most general state space representation of a linear, continuous time dynamical system is given as:

$$\dot{x} = A(t)x(t) + B(t)u(t) \qquad (1)$$
$$y(t) = C(t)x(t) + D(t)u(t)$$

Here x(t) is the state vector representation of the system, u(t) is the vector of real-valued inputs or control variables, and y(t) is the vector of system real-valued outputs. Matrices A, B, C, and D represent the plant or process state transitions, control input transition, state output process, and direct input-output (e.g. disturbances) process respectively (Borgan, 1982). It is possible to incorporate diagnostic information into this controller by altering the controller based on assessed equipment health. For example, if the diagnostic analysis indicates that motor windings are beginning to heat up we may alter the controller to reduce the gain used to define changes in the plant control action. This will result in a system with less stress on the motor windings but at the expense of slightly less system response. We may employ other techniques to shift losses from weakened components to stronger system elements. If it is determined through vibration analysis or current signature analysis techniques that operation is at a critical or resonant frequency, we may alter system speed to avoid such critical frequencies that may accelerate wear of bearing components.

As another example, if we detect that cavitation is occurring we may be able reduce motor speed to eliminate or reduce the severity of this degrading condition. In particular, we may reduce speed to the point that adequate net positive suction head available (NPSHA) is equal to the net positive suction head required (NPSHR). As operating conditions change and NPSHA increases, motor speed may then be automatically increased to the point that maximum flow is one again achieved while NPSHR <= NPSHA. For example, in a tank unloading application we may be able to run the pump at maximum flow when substantial NPSHA is present. As the tank level is reduced we can adaptively reduce the pump speed to optimize throughput while avoiding cavitation. A more detailed example of an integrated diagnostic system with compensating control is described below in the case study.

It is important to note that in the absence of downstream transducers for pressure and speed, we may determine the existence of many pumping problems using only sampled motor current. For example, we may determine the existence of cavitation from a single phase of motor current during pump operation. This is significant since we do not need any pump curves to do this diagnosis and we are potentially more accurate since we are sensing a specific feature indicative of cavitation rather than utilizing pressure, flow, and pump nominal curves. Changes in viscosity, chemical composition, and pump geometry such as from wear, will alter the accuracy of the pump curves. MCSA techniques promise to be more accurate and less invasive than more traditional pressure-flow measurements with pump nominal design information.

Through various diagnostic means such as described above it is possible to determine that an undesirable operating state is occurring or that certain degraded components will result in early machinery failure. Important benefits are possible by automatically altering the control to avoid the higher-stress operating states and thereby extend the useful operating life of machinery.

PROGNOSTICS & CONTROL

Although process optimization has been employed for many years (e.g. dynamic optimization) such as for continuous chemical processing applications, unique and important benefits are possible by utilizing machinery prognostic information to prescribe an optimum control action dynamically.

The benefits of integrated diagnostics and control may be significantly expanded by utilizing information describing the rate of degradation and remaining useful life of machinery under various possible operating conditions. This permits changing the operating mode to achieve a designated operating lifetime. Alternatively, the control can be specified to minimize energy consumption and maintenance costs or to maximize revenue generation. In extreme conditions, the control may specified to achieve performance beyond the normal operating envelope to protect the environment, avoid costly losses, or protect worker safety while insuring that failure will not occur during these extreme operating conditions. Prognostics with control provides the foundation for overall process optimization with regard to objectives such as efficiency, business strategies, maintenance costs, or financial performance.

We propose to extend the control model for the variable speed motor controller by incorporating three additional elements in the control model.

The three elements that augment the control model are:

- Specification of the allowable range of operation
- Diagnostic & prognostic information, and
- Specification of optimal system operation, processing objectives and business objectives

The first element in the control model is the capability to permit operation within a range of process (state) variables. For example, although the desired (i.e. setpoint) flow may be 100 gpm, the process may still effectively run anywhere between 60 gpm and 110 gpm. The specification of the allowable range of operation may include data related to the sensitivity, accuracy, or marginal nature of the operating bound. Probabilistic and time-dependency information may also be included in the boundary specification.

The second element in the extended control model is information relating to the health of the process machinery and its operation along with information on the future health of the machinery such as rate of degradation and remaining useful life. For example, we may determine that the elevated temperature rise in the motor windings will reduce the insulation life by ½ or that the detected level of cavitation will accelerate seal failure by 10 fold.

The third element in the extended control model is an analytic representation of the operating objectives of the process or plant along with any additional operating constraints. The representation of the operating objectives of the process provides a quantifiable measure of the “goodness of operation” and may include critical performance criteria such as energy cost and process revenues. This permits establishing an objective function that may subsequently be optimized through suitable control changes. Additional operating constraints may include data such as noise level, maximum process completion time. An objective function specifying the process and business benefits may be optimized via dynamic changes in the control action subject to not violating any of the process operating constraints.

We can utilize established life expectancy models in conjunction with classical control techniques to control the residual lifetime of machinery. For example, crack growth models based on cyclic loading provide a probabilistic model that can be embedded in a simulation model to determine future stress due to vibration, temperature gradient, and pressure. The Forman deterministic crack growth failure model provides a basis for altering the stress and rate of crack growth directly from changes in the control. The altered control then provides a quantitative measure of the change in crack growth rate. This information can be used to control the expected remaining lifetime of degraded components and insure that failure does not occur before a tank is emptied or a scheduled PM or machinery overhaul occurs.

The focus of prognostics and distributed control will enable future plant operations to be based on proactive operation rather than reactive problem solving. Device alerts initiated from remote intelligent machines will warn of future potential problems giving time for appropriate remedial or preventive action. Integrating machinery prognostic information with automatic, real-time decision making can provide significant opportunities for optimized plant operation.

ASSET OPTIMIZATION

Given that we have suitably defined the permissible operating modes, established a means to project into the future possible or probable operating states, and a criterion for judging preferred or optimal performance we may formulate the problem as a classical optimal control problem (Borgan, 1982).

For example, if the operating objective is to minimize energy cost per gallon pumped then the objective function will include flow information, cost per kWh, and motor-drive power consumed. Dynamic changes may be made to both the motor speed and drive internal parameters to optimize the cost per gallon pumped subject to previously defined process constraints. It is important to note that the operating example above will result in the least energy cost per gallon pumped however, it may also result in accelerated wear or thermal degradation of critical machinery components. A more comprehensive operational model and objective function may incorporate these additional parameters if required. Additional parameters may include information such as expected failure rate and failure cost for different operating modes, machinery lifetime and capital replacement costs, and the impact on other connected machines and processes such as valves, piping, and other process machines.

Our objective is to establish a control method that will support decision making at each decision time interval or control iteration loop. Bellman’s principle of Dynamic Programming specifies that if the system is at some intermediate point on an optimal path to a goal then the remainder of the path must be on an optimal path from the intermediate point to the goal (Billingsley, 1989). Although apparently a simple concept, this permits making optimum choices of the control variable, $u(t)$, at time t by only considering the need to drive the system from state $x(t)$ to $x(t_f)$, the final state of the system. This approach provides an efficient technique for sequential decision making while insuring that the complete system trajectory will be optimal from time t0 to t_f and we do not need to consider all possible control options at every decision point simultaneously.

We can formulate the optimization problem as:

$$\text{Min } J = S(x(t_f), t_f) + \int_{to}^{tf} L(x(t), u(t), t)dt \qquad (2)$$

$$\text{Subject to } f(x(t), \dot{x}(t), y(t), u(t)) = 0 \text{ where } t \in [t_0, t_f]$$

with defined initial conditions, time constraints, control variable and state variable constraints (Borgan, 1982). Here J represents the objective function value to be minimized (or maximized). S and L are real-valued functions with S representing the cost penalty due to the stopping error at time t_f (e.g. wasted fluid not pumped or discarded useful life in replaced equipment). L represents the cost or loss due to transient errors in the process and the cost of the control effort during system operation.

For example, if we put the value of the stopping cost function S = 0 and L = $u^t u$ then we get:

$$\text{Min } J = \int_{to}^{tf} u^t u \, dt \qquad (3)$$

Equation 3 is a measure of the control effort or energy expended for a process operating from time t_o to time t_f. This is termed the least-effort problem and in the case of a drive-motor-pumping system, results in completing a process segment (e.g. emptying a tank) at the lowest possible energy cost.

When J is differentiable, we may use gradient search techniques to compute the desired change in control, u(t), that moves J closer to the minimum (or maximum value). The concept of the gradient is significant in that the change in the objective function we obtain from a suitable control u(t) is proportional to the gradient, grad(J). This provides a specification for the change in u needed to move J closer to the optimum (Hillier and Lieberman, 1974).

If J is convex then we need not worry about local optimum values and any optimum value we obtain is a global optimum. This formulation permits a step-by-step evaluation of the gradient of J and the selection of a new control action to drive the system closer to an optimum. The gradient search technique, also called the method of steepest decent, is illustrated graphically in Figure 4. Here each arrow represents a new control decision in the quest to realize a minimum value for the objective function, J.

The specification of the optimal performance metric, J, can incorporate information beyond energy utilization, maintenance cost, or longevity of operation. For example, it is possible to also formulate J to include strategic business information and asset value information. In this manner selecting the sequence of optimal control actions u(t) to optimize J will drive the system to achieve optimum utilization of the assets involved.

It is possible to include the cost of maintenance for various failure modes, replacement and installation costs, maintenance strategies, cost for scrap, re-work, line-restarting, and revenue generation from the specified machinery. This permits the generation and implementation of optimal asset lifetime management policies across critical plant assets. The operational success of this approach requires an effective asset register base, observability of key state variables, and viable process and component models (Hoskins, et al., 1997). The utilization of open, industry standards for asset registry provides important capabilities for integrating operating information across a manufacturing plant and even across facilities. Recent developments have resulted in an Open Systems Architecture for Condition-Based Maintenance that provides a framework for the real-time integration of machinery health and prognostic information with decision support activities. This framework spans the range from sensor input to decision support (Discenzo, et al., 2001). This architecture specification is open to the public and may be implemented in a DCOM, CORBA, or HTTP/XML environment.

Often complex business and operational decisions are difficult to incorporate into a single, closed-form objective function. In this case, operating decision and control objectives may be decomposed into a suite of sub-problems such that when taken together, the overall, more complex problem is solved. For example, we may decompose a process into a pumping process, chemical reaction, and storage / batch transport problem. We may treat these as individual sub-problems and optimize each of these subject to boundary or interaction constraints between each sub-problem. Alternatively, we may treat the decomposed problem as a collection of coupled decisions and seek an optimum that balances possibly conflicting objectives and establishes a compromise decision or control that is in some sense optimally global. For example, the industry-wide drive to improve capital equipment utilization and enhance RONA values may be in conflict with reducing maintenance costs and maximizing revenue generation per energy unit consumed. Established techniques for solving coupled and un-coupled optimization may be employed to insure overall asset optimization.

The trend toward distributed intelligence has resulted in the development of intelligent machines that include local, self-diagnostic capabilities. Examples of intelligent, self-diagnosing machines include smart valves (Marritt, 2001) and an Intelligent Motor with embedded sensors, processor, and diagnostic algorithms (Discenzo, et al., 2000). Future Intelligent machines are ideal platforms to deploy local, machinery specific diagnostic algorithms. Intelligent machines are becoming more prevalent due to the low cost of remote distributed compute power and the growing opportunities for low cost interconnectivity such as with wireless operation. In the future these devices promise to significantly enhance operational in safety, environmental protection, and machinery availability (Menezes???).

The proliferation of distributed computing systems and enhanced prognostic, control, and optimization techniques promise to change the landscape of industrial automation systems. An emerging framework that complements the technical capabilities for asset optimization is an agent based representation. Agents may be considered autonomous, intelligent devices with local objectives and local decision making. These agents are however part of a larger collection of agents and possess social and collaborative decision making as well. These capabilities permit localized, distributed agents to collaborate and respond to new, possibly unforseen, operationing conditions. In addition, through collaboration, some agents may choose to operate in a sub-optimal mode in order to achieve some higher level objective such as asset optimization, process safety, or overall process energy optimization.

DEMONSTRATION SYSTEM & CASE STUDY

We have developed a pumping system that integrates diagnostic information with closed-loop control. The integrated diagnostic and control functions are embedded in an intelligent motor control device shown in Figure 5. Integral to this device is a control function, diagnostics function, integration / optimization function, human-machine interface (HMI) function and communications function.

Each of these functions operate in parallel continuously monitoring, assessing, and dynamically controlling the pump system. The keypad permits the operator to get and set operating parameters and process constraints. These values along with dynamic process conditions are displayed on the vacuum florescent display that is shown illuminated in Figure 5. The three color LEDs on the cover illuminate to indicate power applied and running okay, running but at a sub-optimal level, and fault condition – shutdown eminent. The sensor inputs to the diagnostics function consist of input and output pressure, flow, temperature of the fluid, and control parameters including motor power. Pump diagnostics may be based on pressure, speed, and flow values mapped to the pump performance curve to determine NPSHR. Actual measured suction head may used to determine if cavitation is occurring, the severity of the cavitation and the new desired pump speed.

Alternatively, in the absence of any downstream pressure, temperature, vibration, or flow sensors, we may monitor a single phase of motor current and detect the discriminating features from the frequency spectrum of motor current when the symptoms of cavitation actually occur. This approach avoids the using downstream, pump or pipe mounted sensors for pump protection and avoids inaccuracies or approximations that may exist in the pump nominal curves. Installation cost is reduced and accuracy is improved using motor current signature analysis techniques.

The demonstration system, shown in Figure 2, includes a 3-phase, 2 hp, a-c induction motor coupled to a centrifugal pump. When the system operating mode selected is “manual”, the motor-pump system is controlled with a variable speed drive and speed, torque, or other process setpoint value is maintained. Compared to line-fed motor-pump systems we can realize significant energy savings if the process does not continually require full flow rates when running.

The pump system may be switched to “automatic” mode to permit the embedded diagnostic function to not only diagnose machinery health and potentially damaging operation conditions, but also to prescribe a new control action to protect the machinery and drive the system to a new, preferred, optimal operating state. The new operating state is chosen to insure system operation continues within allowable safe operating bounds and that the process is continuing but possibly at a less optimal level. An important control variable is motor speed. By changing motor speed we may control the flow produced, NPSHA, NPSHR, and other parameters such as head, motor temperature, and power utilization for example.

We can treat the intelligent system as a multi-variable control system. In particular, we can change other motor and drive parameters as needed to optimize the established objective function subject to defined operating constraints. Figure 6, Energy Utilization and Motor Temperature at Several Drive Frequencies, shows the changes in energy utilization at several different carrier frequencies for a commercially available variable speed drive.

This data indicates several control variables that may be simultaneously specified to meet processing requirements while optimizing the specified objective function. For example, the objective function may specify minimizing the energy required for a specific processing function such as emptying a tank. In this case, if noise, dynamic performance, or heating is not an issue, we may shift the drive to run using a 2kHz carrier signal and run at a reduced speed.

CONCLUSIONS

The enhanced capability of systems that perform accurate embedded diagnostics and prognostics coupled with the reduction in deployment cost will accelerate the use of distributed intelligent components. Recent interest in model-based diagnostics and prognostics coupled with stochastic and belief methods will provide the accuracy and robustness needed for accurate residual lifetime estimation. Various initiatives for low cost, low-bandwidth wireless connections will directly impact the ability to deploy many small intelligent units on each critical component of a process.

Real time information streaming in continuously from many distributed intelligent devices will readily become overwhelming for traditional, central control and monitoring systems. Distributed control and in particular agent-based system will provide the powerful framework necessary to effectively utilize and manage the massive amount of information readily available. Demonstrations of autonomous, agent-based systems being conducted today show the robustness and important capabilities from localized decision-making coupled with distributed collaboration and accommodation to meet higher-level objectives.

The technologies outlined above represent new and important capabilities that are broadly applicable across a wide range of industrial and commercial systems. These capabilities will significantly change the way machinery and equipment is operated and maintained. The impact will be to effectively integrate low-level machinery information and control with operational objectives and business strategies. We believe this new operational mode will provide the foundation for asset optimization and improved financial performance. Coupling plant floor automation with business objectives for asset optimization will be a defining characteristic of the leaders of tomorrow.

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