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OPTIMIZING, ADAPTIVE PROCESS CONTROL FOR PHOSPHATE FLOTATION

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OPTIMIZING, ADAPTIVE PROCESS CONTROL FOR PHOSPHATE FLOTATION

FINAL REPORT

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PERSPECTIVE

One of the most effective approaches to achieve a significant improvement in processing efficiency is the real-time control of each of the unit operations. Process control systems routinely used in mineral processing were born with the invention of the microprocessor. It is expected that control systems of the future will continue to develop towards user-friendly computer-based systems that use powerful software analysis and control techniques.

At its October 1995 meeting, the FIPR Board of Directors approved funding for a proposal by the former U.S. Bureau of Mines Tuscaloosa Research Center. The project was entitled "Modeling of the Phosphate Beneficiation Process as a Forerunner to Adaptive Control" (FIPR #95-02-103). Since the U.S. Bureau of Mines was shut down permanently in December 1995, the project was carried on by three former USBM employees who formed the consulting firm BCD Technologies.

As a result of that project, BCD has delivered six computer models to simulate a phosphate flotation system. These models have been tested on plant data obtained from the Florida phosphate industry, giving a relatively accurate prediction of phosphate recovery.

The goal of the current project was to develop an optimizing, adaptive process control system for phosphate flotation. The control system is to employ the six computer models of phosphate flotation developed under the above-mentioned FIPR contract. The adaptive controller will take advantages of the graphical user interface developed to allow the computer models to be assembled into realistic circuits. The graphical user interface will play an integral role in the proposed investigation. Ultimately, it will allow users not intimately familiar with the C++ programming language, genetic algorithms, and fuzzy logic to develop computer models and controllers.

An optimizing, adaptive process controller combines the process control capabilities of fuzzy logic with the adaptive capabilities of genetic algorithms. Fuzzy logic is a technique through which a computer controller is implemented using subjective, linguistic concepts similar to human decisionmaking. Genetic algorithms are search algorithms based on processes found in nature. They rapidly locate near-optimal solutions to difficult search and optimization problems.

The adaptive control technology has two major advantages over the conventional stabilized control strategy: it has the learning capability, and does not require a lot of sensory information. Although the project failed to develop a control strategy that can do better than an experienced operator, it came up with a novel concept of establishing a control curve using the ratio of feed grade to fatty acid flowrate.

ABSTRACT

An optimizing, adaptive process control system for a phosphate processing plant has been designed and tested using actual data from an operating phosphate processing plant. The *level-2 intelligent control system* consists of three key elements: (1) a control element, (2) an adaptive element, and (3) a learning element. The controller employs a neural network model of the phosphate plant, a fuzzy logic control element for manipulating the plant, and a genetic algorithm-based search engine. This report presents key background information regarding intelligent control systems, describes the overall architecture of the control system developed, designed, and tested, and presents results demonstrating the effectiveness and potential of the control system. Finally, recommendations are made regarding directions for future development and implementation of optimizing, adaptive control systems in the phosphate industry

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EXECUTIVE SUMMARY

Phosphate flotation plants in the United States are not currently operating at peak performance. This inadequacy must be rectified if America is to continue competing in the world market. The biggest improvements in the efficiency of existing phosphate processing plants in the near future are likely to be made by implementing new and improving existing computer-based process control systems. Many of the most effective process control systems currently being developed and implemented in industry are instances of model-following control systems–systems that utilize computational models of the system to be controlled to make accurate predictions of system behavior. Development of these model-following control systems requires fast and accurate computer models of the system to be controlled. In a recently completed FIPR project entitled, "Modeling of the Phosphate Beneficiation Process as a Forerunner to Adaptive Control," six computer models of phosphate flotation were developed and tested. The current project builds on the aforementioned project via the incorporation of the computer models into an optimizing, adaptive process control system. This report presents details of the optimizing, adaptive process control system, demonstrates its effectiveness and potential by presenting results achieved through the application of the system to an operating phosphate plant, and discusses issues associated with future development and implementation.

In the original modeling effort completed by BCD Technologies, six computer models were developed to simulate a phosphate flotation system. Each of the models were tested and evaluated using plant data obtained from operating phosphate plants. The six computer models included both first-principle and empirical models. First-principle models are based on the actual physics of the system being modeled. They allow the user to investigate the effects of altering parameters outside of the region for which data is available. Empirical models are not necessarily concerned with the physics of the system being modeled. Rather, they are concerned only with accurately modeling the response of the system. After further evaluation of the six computer models developed in the original effort, a neural network model was deemed most appropriate for use in the effort to design, build, and implement an optimizing, adaptive control system. The robust nature and flexibility of the neural network model, combined with the accuracy with which it could model the plant where the control system was implemented made it the most appropriate and most effective model to use.

For many years the industry standard in control systems has been stabilizing control. In this type of control system, various process parameters are driven toward and ultimately maintained at pre-defined setpoints, typically through the implementation of Proportional-Integral-Derivative (PID) controllers. Recently, a tremendous amount of research has been done to move beyond stabilizing control, with a specific focus on developing control systems capable of generating: (1) self-improving tracking errors, (2) adaptive control parameters, and (3) optimized estimates of the performance error. A control system that includes all three of the capabilities listed above is known as a *level-2 intelligent controller*. The control system described in this report is such a control system for manipulating a specific phosphate processing plant.

The level-2 intelligent controller consists of three primary elements: (1) the control element, (2) the adaptive element, and (3) the learning element. The control element is responsible for directly manipulating the various devices in the phosphate plant–for altering the plant parameters. In architecture described here, the control element is based on a fuzzy logic controller. The adaptive element is responsible for recognizing when the unmeasured parameters in the plant have changed, and for quantifying their new state. In the adaptive control system developed, this unit achieves its goals through the use of a genetic algorithm and a neural network model of the plant. The learning element must make adjustments to the control element; adjustments made necessary as a consequence of the changes to the system identified by the adaptive element. In the current system, the learning element employs a neural network model of the plant, a genetic algorithm-based search engine, and a copy of the fuzzy logic control system used in the control element. When fully engaged, the three-element control system performs optimizing, adaptive control.

The fully-developed control system has been tested using data from a functioning phosphate processing plant. The system has not been fully implemented in the plant for a variety of reasons discussed in this report including safety issues, data collection problems, proprietary information agreements, etc. However, when tested using actual plant data, the optimizing, adaptive control system performed on a level equivalent to that of human plant operators. Thus, this system represents a major first-step toward a fully functional optimizing, adaptive control system.

An optimizing, adaptive control system has been developed and tested against data acquired from an operating phosphate plant. During the course of this development, data analysis revealed a relationship between effective plant operation, feed grade, feed throughput, and recovery. This relationship has been captured in an empirical equation, and can potentially be incorporated into a straightforward control system; one that is much simpler to implement than the intelligent control system, and yet still extensible to a variety of plant operations. This strategy is described in the report.

BACKGROUND

Phosphate flotation plants are not currently operating at peak performance; this inadequacy must be rectified if the Florida phosphate industry is to continue competing in the world market. Major improvements in the efficiency of phosphate processing plants in the near future are likely to be made in the area of process control (Karr and Stanley 1992). Many industries are obtaining improved process control by using new methodologies. Many of the most effective process control systems are model-following controllers. These model-following control systems are dependent on the existence of fast and accurate computer models of the system to be controlled. As a precursor to the development of optimizing, adaptive control systems, FIPR sponsored a research project to develop a suite of computer models that can be used to predict the response of phosphate flotation systems (Scheiner, Stanley, and Karr 1996). The result of this preliminary effort was six computer models of phosphate flotation and a comprehensive graphical user interface that contains ports that allow for straightforward attachment to other systems from which a control system can be implemented.

In the mid 1980’s BCD Technology researchers, while employed at the U.S. Bureau of Mines, developed a system of optimizing, adaptive process control (Karr 1991a). The controllers developed using this method combine the process control capabilities of fuzzy logic with the adaptive capabilities of genetic algorithms, two techniques from the field of artificial intelligence. Fuzzy logic is a technique through which a computer controller is implemented using subjective, linguistic concepts so popular in human decision-making. Genetic algorithms are search algorithms based on processes found in nature (Goldberg 1989). They rapidly locate near-optimal solutions to difficult search and optimization problems. Together, fuzzy logic and genetic algorithms provide the capabilities necessary to achieve optimizing, adaptive process control.

The method to optimizing, adaptive process control developed by the BCD Technologies researchers has proven to be extremely robust in that it has been shown to be effective across a spectrum of industries. The first successful implementation of this method occurred on a classic academic problem – a cart-pole balancing problem (Karr 1991b). This problem is often used to model balancing problems associated with two-legged robots. Next, the method was used to solve a difficult pH titration problem from the field of chemical engineering (Karr and Gentry 1992). In this problem, the method was used to develop an adaptive control system that could compensate for the lack of sensory data from the system being controlled which is the case with existing phosphate plants. Next, the method was used to solve another control problem from the field of chemical engineering. Specifically, it was used to control an exothermic reaction used for the production of hexamine (Karr et al.1993). In this application, Karr and his co-workers demonstrated the ability to produce a controller that changed strategies based on current, dynamic economic information. The most recent success of this approach involved the development of an adaptive control system for helicopter flight control which required fast response time (Phillips, Karr, and Walker 1996). In this problem, Phillips, Karr, and

Walker developed a helicopter flight control system that was successfully tested at White Sands Missile Base, NM.

To date, the phosphate industry has not fully embraced adaptive control systems. These controllers have the potential to improve the metallurgical efficiency of phosphate operations and provide flexibility to adapt to changing economic conditions. Additionally, the Florida Phosphate Industry has traditionally employed conventional froth flotation technology. Recently, however, they have funded a project involving column flotation units that can be used to augment or possibly replace traditional froth flotation units. It is important to note that the optimizing, adaptive process control system to developed for traditional flotation units is potentially extensible to column flotation (Karr and Ferguson, 1995). BCD Technologies has developed a first principles computer model of a column flotation circuit (Yeager, Brown, and Stanley 1994) and, in conjunction with the University of Florida, is currently developing a differential equations model of flotation column.

For many years the industry standard in control systems has been stabilizing control. In this type of control system, various process parameters are driven toward and ultimately maintained at pre-defined setpoints, typically through the implementation of Proportional-Integral-Derivative (PID) controllers (Medsker 1995). Recently, a tremendous amount of research has been done to move beyond stabilizing control, with a specific focus on developing control systems capable of generating: (1) self-improving tracking errors, (2) adaptive control parameters, and (3) optimized estimates of the performance error (Miller, Sutton, and Werbos 1991). A control system that includes all three of the capabilities listed above is known as a *level-2 intelligent controller*. The control system described in this report is such a control system for manipulating a specific phosphate processing plant.

The level-2 intelligent controller consists of three primary elements: (1) the control element, (2) the adaptive element, and (3) the learning element. The control element is responsible for directly manipulating the various devices in the phosphate plant--for altering the plant parameters. In architecture described here, the control element is based on a fuzzy logic controller. The adaptive element is responsible for recognizing when the unmeasured parameters in the plant have changed, and for quantifying their new state. In the adaptive control system developed, this unit achieves its goals through the use of a genetic algorithm and a neural network model of the plant. The learning element must make adjustments to the control element; adjustments made necessary as a consequence of the changes to the system identified by the adaptive element. In the current system, the learning element employs a neural network model of the plant, a genetic algorithm-based search engine, and a copy of the fuzzy logic control system used in the control element. When fully engaged, the three-element control system performs optimizing, adaptive control.

REVIEW OF COMPUTER MODELS

In a recently completed FIPR project entitled, "Modeling of the Phosphate Beneficiation Process as a Forerunner to Adaptive Control," BCD Technologies researchers developed and tested six computer models of phosphate flotation. These computer models were written in the C++ computer language and were object-oriented both for maintainability and for extensibility. The modeling system ultimately developed included a graphical user interface that could be used by a user not intimately familiar with the computer modeling methods, search algorithms, and error reduction techniques used in the models. The modeling software is quite complex thus a blackboard system was developed to manage the complexity. This blackboard system coordinated the efforts of the various software modules.

In the current research effort, only the six computer models are of importance. Since, neither the blackboard system nor the graphical user interface was necessary for incorporation into the optimizing, adaptive control system, only the six computer models are reviewed here.

The six computer models that were developed to simulate a phosphate flotation system were tested on plant data obtained from the Florida phosphate industry. These models included both first-principle and empirical models. First-principle models are based on the actual physics of the system being modeled. They allow the user to investigate the effects of altering parameters outside of the region for which data is available. Empirical models are not necessarily concerned with the physics of the system being modeled. They are concerned only with accurately modeling the response of the system.

The first computer model is a first-principle model originally developed by Jordan and Spears (1990). This model is in effect a standard model for flotation in conventional cells because it is based on a few decades of world-wide research. This computer model used particle sizes, particle densities, bubble sizes, relative velocities, and induction time to compute three probabilities generally associated with flotation: (1) the probability of a bubble-particle collision, (2) the probability of a particle adhering to a bubble, and (3) the probability of a particle remaining attached to a bubble. The model subsequently used these probabilities in conjunction with two additional measured probabilities to compute an expected recovery.

The second and third computer models are statistical models. These models utilize various statistical tools to analyze the data obtained from the flotation system. These tools include regression analysis, factor analysis, cluster analysis, and projection to latent structures. The statistical models provide very little insight into the physics of the flotation system. However, they are very useful in exploring the structure of data. They can identify different physical mechanisms contributing to the data elements and allow insight into the extent and nature of the error associated with the data.

The fourth computer model is a neural network model. Neural networks are approximate models of the human brain in which computational elements called neurons are placed in a network of weighted connections called synapses. These networks are then trained on existing data to accurately reproduce the response of the system. Neural networks produce very powerful and very flexible models. Unfortunately, they are the ultimate "black box"; they give no indication why a particular input produces a given output.

The fifth computer model is based on fuzzy logic and genetic algorithms. Fuzzy logic is a technique that allows computers to manipulate subjective, linguistic concepts like those commonly used in human decision-making. Genetic algorithms are search algorithms based on the mechanics of genetics. They are robust algorithms that have been used successfully to solve a wide range of problems. Together fuzzy logic and genetic algorithms were shown to be capable of accurately modeling phosphate flotation plants from relevant plant data. Although the performance of this model is similar to that of the neural network model, it is not a black box. The fuzzy model gives a clear explanation of its reasoning in the form of linguistic rules.

The last computer model is a rate constant model. The rate constant model, like the first-principle model, consists of a collection of simple first-order differential equations. But instead of basing the computation of the rate constants for the differential equations on a model of the underlying physical processes, the rate constant model fits them statistically from plant operating data. The only independent variables in this model's differential equations are the concentrations of mineral species in the feed slurry. This model requires the plant data observations to be partitioned into clusters, each representing the same kind of operating conditions. Rate constants are then computed for each cluster. Thus, the rate constant model consists of several sets of rate constants along with a rule for choosing the appropriate set for any given operating state for the plant.

Of the six computer models available, the neural network model was deemed to be the most appropriate modeling tool for the current effort. The first-principle model, the two statistical models, and the general rate constant models all proved to require excessive statistical analysis of the plant data to adequately model the phosphate operations. In efforts simply to model plant operations, this requirement is not a major undertaking. However, to be effectively used in the current effort to design an optimizing, adaptive control system, this effort made the computer models too sluggish. The self-generating fuzzy linguistic model, on the other hand, proved to be both accurate enough and extensible enough to be used in the current effort. In fact, this modeling approach proved to have some very desirable attributes. Namely, it produced modeling laws that could be easily extracted to gain insights into the inner-workings of the phosphate plant. However, this computer model proved to take longer to train than the neural network model that was ultimately chosen for use in the optimizing, adaptive control system. The neural network model proved to be both accurate and easily extensible to general phosphate plant modeling efforts. Thus, the neural network model was selected as the most appropriate modeling agent for use in the development of an optimizing, adaptive control system.

Since the ability to accurately model plant operations is vital to the adaptive control system, efforts were made to improve the capabilities of the neural network in this domain. Results depicting the effectiveness of this computer model are therefore included in a later section of this report.

LEVELS OF INTELLIGENT CONTROL--AN OVERVIEW

Ever since computers were invented, researchers have been striving to develop machines that are capable of learning. Recently, these efforts have begun to influence the development of control systems. Currently, the emerging fields of modern control and of intelligent control are focused on developing control systems that are capable of adapting to rapidly changing environments and of improving their performance based on their experience. In other words, modern control systems are being developed that are capable of learning to improve their performance over time (to learn) much like humans do. The system described in this report is an example of an intelligent control system. This section reviews the fundamentals and basic levels of intelligent control.

There are several terms used in the field of process control that are important in understanding the various levels of intelligent control. First, *tracking error* is the term used to mean the difference between the current value of a given system parameter and the stated desired value of said system parameter (the setpoint value for said parameter). Second, the *control parameters* are values of coefficients used in the control system to make adjustments to the system being controlled. These values are typically things like gain constants in traditional controllers. In adaptive controllers, the control parameters vary widely depending on the form of the control laws employed. Third, the *performance measure* is an expression of how well the controller is doing at achieving its goal. This might be exactly the same as the tracking error in a simple control system, or it might be a highly complex depiction of the state of the system as it relates to current values and future goals. Fourth, *planning function* is an expression of the potential long-term goals of the control system, and the mechanism by which the control system will improve its tracking error, its control parameters, and/or its performance measure. Given these definitions, distinct levels of intelligent control systems can be defined.

A level 0 intelligent control system is one that is capable of improving its tracking error. This can be achieved in a variety of ways including employing a simple search algorithm to improve the gain constants in a traditional controller. Level 0 intelligent controllers typically provide robust feedback control in that they efficiently drive system error to zero and are capable of managing perturbations to the system being controlled.

A level 1 intelligent control system is one in which self-improvements are made to both the tracking error and the control parameters. These intelligent controllers typically provide robust feedback control with adaptive control parameters. The error associated with these controllers tends to zero for non-nominal operations. Basically, it is a control system in which the feedback is self-improving. The mechanisms for achieving this type of control are varied, but include neural networks, fuzzy systems, and adaptive critics.

A level 2 intelligent control system must contain all of the characteristics of a level 1 intelligent control system and also include an internally-generated performance measure. These controllers are robust, adaptive feedback control systems in which a utility function is minimized (or maximized) over time. These controllers drive a tracking error to zero while simultaneously optimizing a performance measure. The optimizing, adaptive control system described in this report is an instance of a level 2 intelligent control system.

Few, if any, level 3 intelligent control systems have been developed and implemented on real-world systems. These controllers contain all of the characteristics of a level 2 intelligent control system and also include a planning function. They have the ability to plan ahead for certain situations, and can also autonomously simulate and model uncertainties that might appear in the system being controlled. This level of intelligent controller exhibits many of the attributes that make humans such effective controllers.

The optimizing, adaptive control system described in this report is a level 2 intelligent control system. It employs a set of control laws to effectively manipulate a phosphate processing plant. These control laws drive a tracking error to zero. In addition, the current controller has the ability to manipulate its own control parameters via the use of a genetic algorithm. And, it minimizes a utility function, which here represents basically a cost function. The architecture of this level 2 intelligent control system is described in the following section.

AN ARCHITECTURE FOR ACHIEVING OPTIMIZING, ADAPTIVE CONTROL

The optimizing, adaptive controller described in this report combines several biologically oriented techniques into a comprehensive approach to adaptive process control. The three specific techniques from the field of artificial intelligence used to produce the adaptive process control systems are: (1) fuzzy logic, (2) genetic algorithms, and (3) neural networks. Fuzzy logic is a technique in which the human "rule-of-thumb" approach to decision making is modeled. Genetic algorithms are search algorithms based on the mechanics of natural genetics that are able to rapidly locate near-optimum solutions to difficult problems. Neural networks are crude paradigms of the mammalian brain that have been used to model industrial systems. This section provides an overview of the architecture used to achieve adaptive process control.

BACKGROUND MATERIAL

Economic stresses are forcing numerous industries to implement systems that employ emerging computer technologies. Many of these industrial systems are difficult to manage with conventional computer based process control strategies because these strategies lack an effective means of adapting to changes in the problem environment. Furthermore, conventional mathematical tools employed for process control can be extremely complex even for simple systems. Thus, researchers are beginning to explore the use of biologically motivated computer techniques such as fuzzy logic, genetic algorithms, and neural networks to solve difficult process control problems. This paper describes a comprehensive approach to intelligent, adaptive computer based process control that incorporates the strengths of the three biologic models mentioned above.

Fuzzy logic controllers (FLCs) are being used successfully in an increasing number of application areas, including cement kiln control, task scheduling, and robot arm manipulation (Evans, Karwowski, and Wilhelm 1989; Turksen 1990). These rule-based systems incorporate *fuzzy linguistic variables* into their rule set to model a human's "rule-of-thumb" approach to problem solving. FLCs include rules to direct the decision process and membership functions to provide linguistic terms with the precise numeric values required in most application areas. Since both the rule set and the membership functions play an integral role in determining the control action, a FLC can be provided with adaptive capabilities by altering either the rule set or the membership functions.

The approach that has generally been adopted for producing adaptive FLCs is to alter the associated rule set. Procyk and Mamdani (1978) developed an adaptive FLC that utilizes the system Jacobian (composed of derivatives) to alter its rule set. Unfortunately, determining an adequate representation of the system Jacobian for complex industrial systems can be extremely difficult if not impossible because of the imprecise measurements and changing conditions in the systems. Galluzzo, Cappellani, and Garofalo (1991) developed an adaptive FLC for managing a pH titration system. Their FLC altered its rule set via a supplementary set of very general rules that served in a supervisory capacity taking into account information concerning the performance of the controller. These adaptive FLCs, and systems like them that alter a rule set, have performed well and show great promise in the area of industrial process control.

Researchers at BCD Technologies developed a technique for producing adaptive FLCs in which the focus is on altering the FLC's membership functions rather than its rules. This approach produces a more robust control system that is applicable in numerous application domains (Karr 1991a). Genetic algorithms (GAs) are search algorithms based on the mechanics of natural genetics (Goldberg 1989). They have a demonstrated ability for altering membership functions in response to changes in the problem environment to produce more efficient FLC performance (Karr 1991a). Furthermore, GAs are capable of altering the control strategies encoded in FLCs in real-time without requiring derivative information. The only requirement of the GA is a computer model of the problem environment so that potential control strategies can be evaluated. Certainly, producing a computer model of modern industrial systems can be an imposing task. This task can be accomplished by employing a third biologic paradigm, a neural network.

Neural networks prove to be powerful tools for discerning functional relationships, and can be used for modeling industrial systems. In fact, neural network models of industrial systems can be developed with minimal knowledge of the functional relationships between the parameters in the system to be modeled (Wasserman 1989). This is an important attribute in developing computer simulations of industrial systems because it is generally extremely difficult to provide accurate first principle models of such complex systems. Thus, a neural network's ability to discern functional relationships, and thus to provide a computer simulation of a plant or operation, is a vital component of the process control system presented as well as in other model based control systems. A neural network model developed for simulating the performance of a phosphate plant developed under a previous FIPR grant discussed in the Introduction is used in the current study.

Each of the three biologic paradigms discussed above serve a definite purpose in the control system to be discussed. First, a simple FLC is used to manipulate the problem environment. Second, a GA is used to search for fuzzy membership functions that are more efficient than those being used by the FLC. Third, a neural network is used to simulate the problem environment so that the GA will have a vehicle for evaluating potential new membership function sets. Naturally, a control system of this complexity is not required in stable, imperturbable problem environments.

The remainder of this section described the particulars of the software architecture developed for achieving optimizing, adaptive process control.

SYSTEM ARCHITECTURE

Figure 1 shows a schematic of the fundamental architecture used to achieve, optimizing, adaptive control. The heart of this control system is the loop consisting of the control element and the problem environment. The control element receives information from sensors in the problem environment concerning the status of the *condition variables* (also termed state variables or controlled variables depending on the field of study) which detail the current state of the system. It then computes a desirable state for a set of *action variables* (also termed manipulated variables). These changes in the action variables force the problem environment toward the setpoint. This is the basic approach adopted for the design of virtually any closed loop control system, and in and of itself includes no mechanism for adaptive control.

The adaptive capabilities of the system shown in Figure 1 are due to the analysis and learning elements. In general, the analysis element must recognize when a change in the problem environment has occurred. A "change," as it is used here, consists of a perturbation to the system that causes the problem environment to react differently to control actions. Also, such a change must involve parameters that are not included in the list of condition variables; if they were included in the list of condition variables, then the control element could account for the perturbations. The analysis element uses information concerning the condition and action variables over some finite time period to recognize changes in the environment and to compute the new performance characteristics associated with these changes.

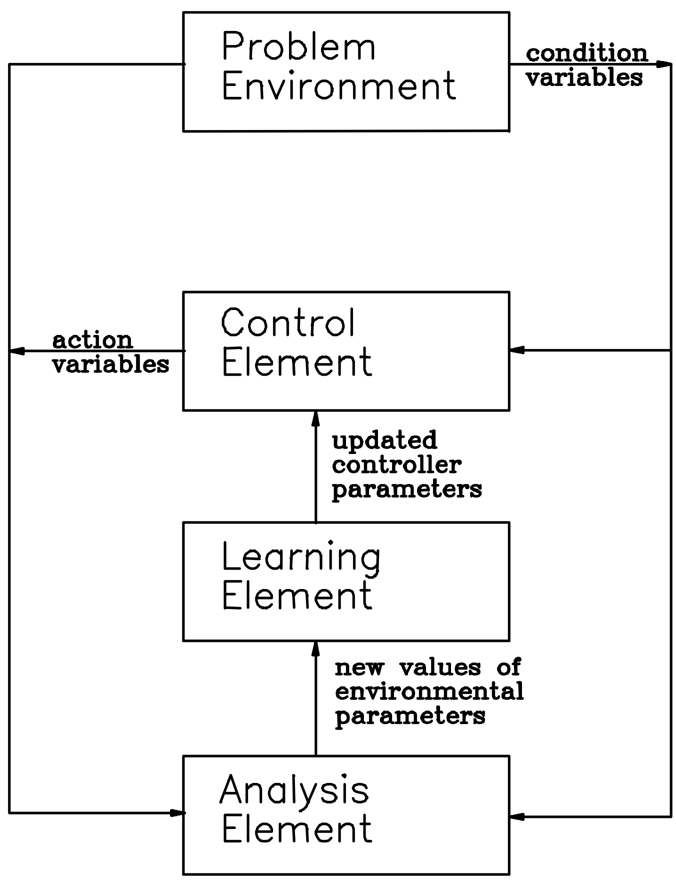

Figure 1. The Architecture Used to Implement the Optimizing, Adaptive Control System Consists of Three Main Elements: (1) Control Element, (2) Analysis Element, and (3) Learning Element.

The new environment (the problem environment with the altered parameters) can pose many difficulties for the control element, because the control element is no longer manipulating the environment for which it was designed. Therefore, the algorithm that drives the control element must be altered. As shown in the schematic of Figure 1, this task is accomplished by the learning element. The most efficient approach for the learning element to use to alter the control element is to utilize information concerning the past performance of the control system. The strategy used by the control, analysis, and learning elements of the stand-alone, comprehensive adaptive controller used in the current effort is provided in the following sections.

Control Element

The control element receives feedback from the problem environment, and based on the current state of the environment, must prescribe appropriate values of the action variables (appropriate control actions). Any of a number of closed-loop controllers could be used for this element. However, because of the flexibility needed in the control system as a whole, a FLC is employed. Like conventional rule-based systems (expert systems), FLCs use a set of production rules that are of the form:

IF {*condition*} THEN {*action*}

to arrive at appropriate control actions. The left-hand-side of the rules (the *condition* side) consists of combinations of the controlled variables; the right-hand-side of the rules (the *action* side) consists of combinations of the manipulated variables. Unlike conventional expert systems, FLCs use rules that utilize fuzzy terms like those appearing in human rules-of-thumb. For example, a valid rule for a FLC used to manipulate a simple pH titration system is:

IF {pH is **VERY ACIDIC** and ΔpH is **SMALL**} THEN {Q_{BASE} is **LARGE** and Q_{ACID} is **ZERO**}.

This rule says that if the solution is very acidic and is not changing rapidly, the flow rate of the base should be made to be large and the flow rate of the acid should be made to be zero.

The fuzzy terms are subjective; they mean different things to different "experts," and can mean different things in various situations. Fuzzy terms are assigned meaning via fuzzy membership functions (Zadeh 1973). As will be seen shortly, the learning element is capable of changing these membership functions in response to changes in the problem environment. The membership functions are used in conjunction with the rule set to prescribe single, crisp values of the action variables. Unlike conventional expert systems, FLCs allow for the application of more than one rule at any given time. The single crisp action is computed using a weighted averaging technique that incorporates both a *min-max* operator and the *center-of-area* method (Karr 1991a).

Analysis Element

The analysis element recognizes changes in parameters associated with the problem environment not taken into account by the rules used in the control element. These changes can, potentially, dramatically alter the way in which the problem environment responds to the control actions, thus forming what is virtually a new problem environment requiring an altered control strategy. One of the main driving forces behind this approach is to keep the control element as small and as simple as possible. A small control element, one with a limited number of rules, allows for faster response times; a simple control element, one without special rules inserted to handle conditions that are not normal, is easier to maintain. The control element must be altered, because in maintaining a control element of limited size and complexity, some of the parameters that affect the problem environment are necessarily left out of the rule set. But before the control element can be altered, the control system must recognize that the problem environment has changed, and compute the nature and magnitude of the changes.

The analysis element recognizes changes in the system parameters by comparing the response of the physical system to the response of a model of the problem environment. In general, recognizing changes in the parameters associated with the problem environment requires the control system to store information concerning the past performance of the problem environment. This information is most effectively acquired through either a database or a computer model. Storing an extensive database can be cumbersome and requires extensive computer memory. In general, the equations describing complex industrial systems are not available. And, as discussed in the section “Review of Computer Models” presented earlier in this report, the neural network model is best suited to serve as a model of the phosphate flotation plant to be controlled.

In the approach to control adopted here, a computer model predicts the response of the actual problem environment using a neural network model. This predicted response is compared to the response of the actual problem environment. When the two responses differ by a threshold amount over a finite period of time, the actual problem environment is considered to have been altered.

When the above approach is implemented, the problem of computing the new system parameters becomes a curve-fitting problem (Karr, Stanley, and Scheiner 1991). The parameters associated with the computer model produce a particular response to changes in the action variables. The parameters must be selected so that the response of the model matches the response of the actual problem environment.

An analysis element can be forged in which a GA is used to compute the values of the parameters associated with the problem environment. When employing a GA in a search problem, there are basically two decisions that must be made: (1) how to code the parameters as bit strings and (2) how to evaluate the merit of each string (the fitness function must be defined). The GA used in the analysis element employs concatenated, mapped, unsigned binary coding (Karr and Gentry 1993). Both the coding and the fitness function employed depend on the particular problem environment being considered. In this current application, the coding scheme is a standard concatenated, linearly mapped, binary coding scheme is used. Also, the fitness function is a relatively standard least-mean-squares approach. Both the coding scheme and the fitness function used are described in detail in an article by Karr (1991a).

Learning Element

The learning element alters the control element in response to changes in the problem environment. It does so by altering the membership functions employed by the FLC of the control element. Since none of the randomly altered parameters appear in the FLC rule set, the only way to account for these conditions (outside of completely revamping the system) is to alter the membership functions employed by the FLC. These alterations consist of changing both the position and location of the triangles and trapezoids used to define the fuzzy terms.

Altering the membership functions (the definition of the fuzzy terms in the rule set) is consistent with the way humans control systems. Quite often, the rules-of-thumb humans use to manipulate a problem environment remain the same despite even dramatic changes to that environment; only the conditions under which the rules are applied are altered. This is basically the approach that is being taken when the fuzzy membership functions are altered. The current system uses a GA to alter the membership functions associated with FLCs, and this technique has been well documented (Karr 1991a).

Summary

The three-tiered architecture used in the current project is effective, flexible, and extensible to a wide range of industrial systems. The system employs a control element to manipulate the phosphate flotation plant, an analysis element to determine when and by how much unmeasured system parameters within the plant change, and a learning element to adjust the control element in response to the unmeasured parameters. This controller architecture proves to be effective, and can be used in a variety of phosphate plants. Although in principle, the system could be developed almost in a generic sense (so that little to no adjustments would be needed to implement the system in any plant), in reality the particulars of the control system depend heavily on the sensors available within the phosphate plant being controlled. The issue of data acquisition is actually terribly important, and is considered in detail in the following section.

ISSUES ASSOCIATED WITH DATA COLLECTION

Perhaps the major issue to be addressed in the development of an optimizing, adaptive control system is data acquisition. In general, the more data available regarding a particular plant's operation, the better the chance of effectively implementing an adaptive control system since the control system relies so heavily on the accuracy of a computer model of plant operations. The phosphate plant at which the current effort was undertaken was at Swift Creek Mine located in the vicinity of White Springs, Florida. This plant is well instrumented, and tends to operate at a high level of efficiency, thus making it an effective arena in which to develop, test, and implement an optimizing, adaptive control system.

Plant Flow Sheet

Based on the information and data obtained from Swift Creek plant engineers, a flow sheet of the plant was formulated. The diagram of the flow sheet shown in Figure 2 depicts the basic operation in which feed comes from two different draglines, labeled as an East Feed and a West Feed. Of course, both feed streams are split into fine and course material resulting in the creation of four streams. After passing through a rougher flotation process, the two course streams are combined into a single line. The resulting three lines are then conditioned, and sent through an amine flotation process.

The Swift Creek Mine operation is generally regarded as a well-instrumented plant. The flow sheet schematic of Figure 2 includes information about the data collection capabilities. Specifically, the points at which sensors in the plant collect information are labeled on the schematic. In this figure, the "M" symbols represent points at which mass flow measurements are taken. The "A" symbols represent points in the plant at which BPL analyses, either by NMR or by chemical methods is available. It is important to note that a number of streams are not measured or analyzed at all, and some measurements were taken only after combining two or more streams.

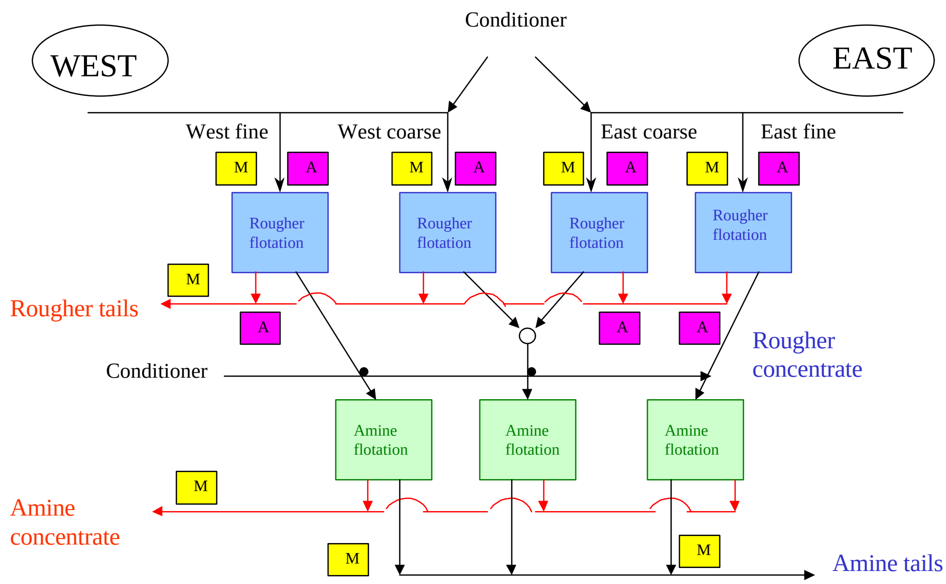

Figure 2. The Flowsheet Above Shows the Points at which Information Is Available. Here, the "M" Symbol Indicates Points at which Mass Flow Rates Are Measured While the "A" Symbol Indicates Points at which Complete Metallurgical Analysis Is Available.

The available data indicated in Figure 2 was not collected with the specific goal of modeling the plant; rather it represents data taken in the normal operation of the Swift Creek plant operation. This fact is evident in the absence of some key information required in the development of a computational model. For instance, nowhere is concentrate grade or recovery measured directly, and there are not enough measurements to calculate mass balances for each, i.e., west fines, west course, etc. However, mass-balanced values for each of the streams are available where the information is aggregated over 8-hour shifts for the same day as the on-line data. Thus, the first requirement for developing a computational model is a data model that can complete mass balances for the real-time data in a way that is consistent with what is known about plant experience and history.

DATA MODEL DEVELOPMENT: COMPLETING THE MASS BALANCE

One of the first points that becomes apparent in considering the information presented in Figure 2 is that there is not enough data available to effectively model the Coarse Rougher and Coarse Amine circuits. The approach described below was applied to both Fine Rougher circuits, achieving correlations between modeled and measured tails BPL of 0.90 and 0.86.

Real-time data was collected everywhere it was available, but only a limited portion of it was actually used in the modeling and control effort. Measured values include flow volumes and some densities, conditioner pH, water pressures, tank levels, valve settings, and pump amps, as well as the online NMR BPL measurements. Because the real-time data system has a limited number of channels of information, all of which are in use, the measurements are taken where they will most help the human operators monitor and control the plant, and to recognize malfunctioning units. Since the major focus of the instrumentation plan at the plant is to achieve stabilizing control, there is a real shortage of the type of data required in a comprehensive modeling effort. In particular, there are almost no measurements between a rougher and its corresponding cleaner (amine) process, and many of the flow rate readings represent combinations of flows from multiple processes.

On-line measurement data was available as recorded for each minute of one 24-hour period at Swift Creek Mine. The data consists of the following information:

- rougher feed volume, specific gravity, and calculated solids mass flow rates;
- rougher conditioning fatty acid, diesel, and ammonia flow PID controller settings;
- rougher tails BPL (note this is the *only* outcome measure for the roughers);
- cleaner conditioning amine and diesel flow rates;
- cleaner concentrate volume, specific gravity, and calculated solids mass flow rates.

Although the on-line analysis values are recorded every minute, they are updated only every fifteen minutes or so. The feed mass flow rate values, in contrast, are very noisy. Thus, these values were "smoothed" using 15-minute averages. Also, stretches of time (covering 2/3 or more of the day) were identified in which the recorded feed BPL, tails BPL, and fatty acid flow rates are constant. The feed mass values were averaged over each such period, then these average (smoothed) observations were used to tune the model parameters.

The mass-balance model must be based on reagent flow data, just as the control model is. The available data supports modeling for control by adjusting fatty acid and amine flows, only: there is not enough variation in other reagent flows, and no data bears on other points of operator control. Therefore, a model is required that can predict concentrate mass flows (or equivalently grade and recovery) based on the flow of one reagent. Reagent flow is measured in gallons per minute, and it must be scaled by the quantity of solids in the feed flow. Since expectations are that a slight increase in sand will result in a very different effect on recovery from a slight increase in apatite, the model needs its first empirical constant: rougher recovery depends on

$$f = \frac{FattyAcidGPM}{c_0\ ApatiteTPH + (2 - c_0)\ SandTPH}. \qquad (1)$$

Moreover, there are numerous unmeasured sources of variation in recovery: changes in particle-size distribution, suspended clay or dissolved phosphate in the make-up water, variation in percent solids or residence time in the conditioning phase, etc. All of these factors can be accounted for with an empirical coefficient, $g(t)$. Expectations are that variations will occur *slowly* over time, which says that the reagent is only partially effective. Rougher recovery depends on

$$r = g(t)\, f = g(t) \frac{FattyAcidGPM}{c_0\ ApatiteTPH + (2 - c_0) SandTPH}. \tag{2}$$

Experience indicates that the recovery function should follow an s-shaped curve: at very low reagent levels there is not enough reagent to float anything, and at very high levels virtually everything has already been floated, so at both extremes the response to adding a little more reagent is quite flat. A function with this form is

$$F(r) = c_1 + \frac{c_2}{1 + c_3 \exp(-c_4 r)} \tag{3}$$

where the c_i's are empirical constants.

One function of this form is used to calculate the apatite recovery, i.e., the variable identified as apatiteInConcentrate/apatiteInFeed. A second separate function is used to calculate the sand recovered, e.g., sandInConcentrate/sandInFeed. The two functions used are:

$$Rcvy_{Apatite}(r) = c_1 + \frac{c_2}{1 + c_3 \exp(-r)} \tag{4}$$

and

$$Rcvy_{Sand}(r) = c_4 + \frac{c_5}{1 + c_6 \exp(-c_7 r)}. \tag{5}$$

A formula for the empirical coefficient $g(t)$ is also needed. Since it is possible to approximate any smooth function to any desired accuracy using sums of sufficiently many sine and cosine terms, two adjustable cosine terms were used:

$$g(t) = a_0 + a_1 \cos(a_2 + a_3 t) + a_4 \cos(a_5 + a_6 t). \qquad (6)$$

A rough idea can be formed about how effective this approach is likely to be even before estimating any empirical coefficients. Since fatty acid flows are fairly steady and $g(t)$ should not change too rapidly, $Rcvy_{Apatite}$ and $Rcvy_{Sand}$ should be fairly stable too. But the ratio $\dfrac{1 - Rcvy_{Sand}}{1 - Rcvy_{Apatite}}$ is the same as $\dfrac{\left(\dfrac{1}{tailsBPL} - 1\right)}{\left(\dfrac{1}{feedBPL} - 1\right)}$, and on-line measurements for tails BPL and feed BPL for rougher processes are available. Figure 3 shows this ratio for the West Fine rougher circuit at the Swift Creek Mine. This graph certainly does not look like one slowly varying function of time, but it *might* show two such functions superposed on one another. Since this rougher process is fed by two draglines some distance apart, there could be a justification for such a finding. Thus, the model actually fitted has not one $g(t)$ function but two, and the computer model employed in the adaptive controller selects whichever one does a better job of matching the observed tails BPL at each point. Figure 4 shows the two functions available to fit the models. Figure 5 shows the effectiveness of this approach in allowing the model to fit the West Fine Rougher circuit target Tails BPL – the model correlation factor is 0.9.

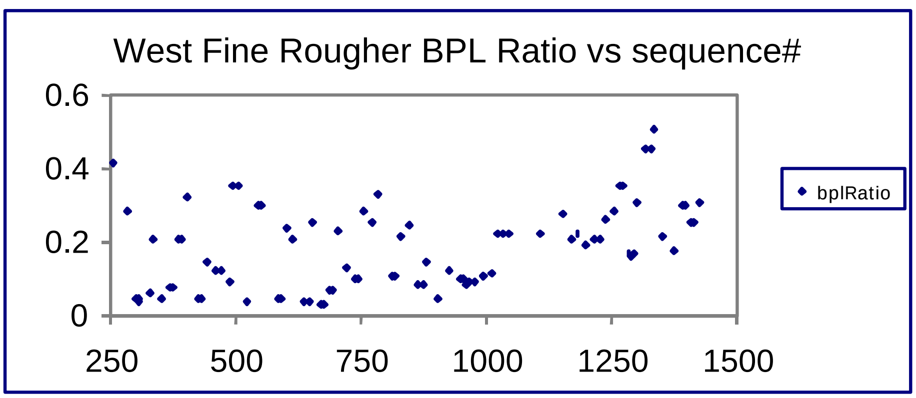

Figure 3. The Fact that the Data Above Does Not Appear to Be a Slow-Varying Function of Time Indicates that There Are Actually Two Functions Present.

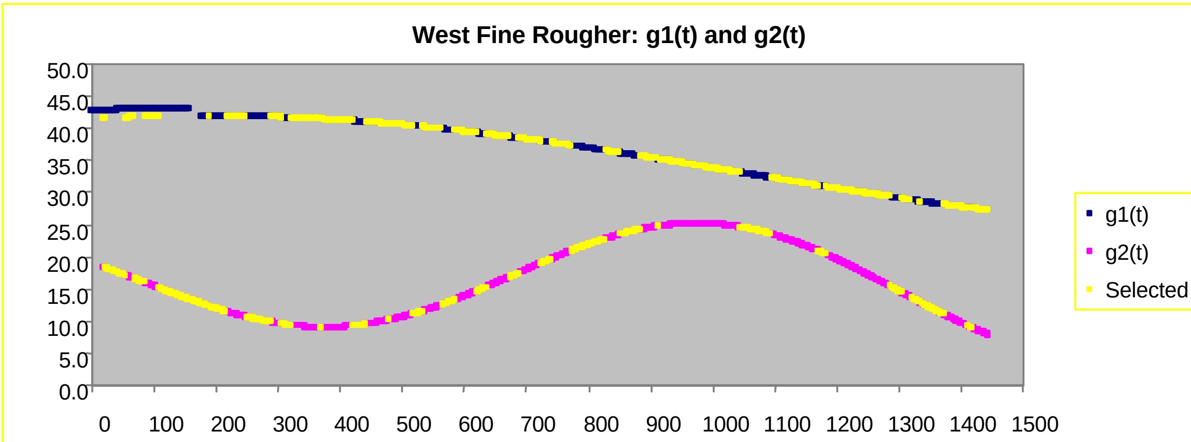

Figure 4. The Approximating Functions Shown Above Were Developed Using a Computational Model of the West Fine Rougher Circuit. This Figure Indicates that the Approximating Functions Accurately Simulate the Performance of the Plant System.

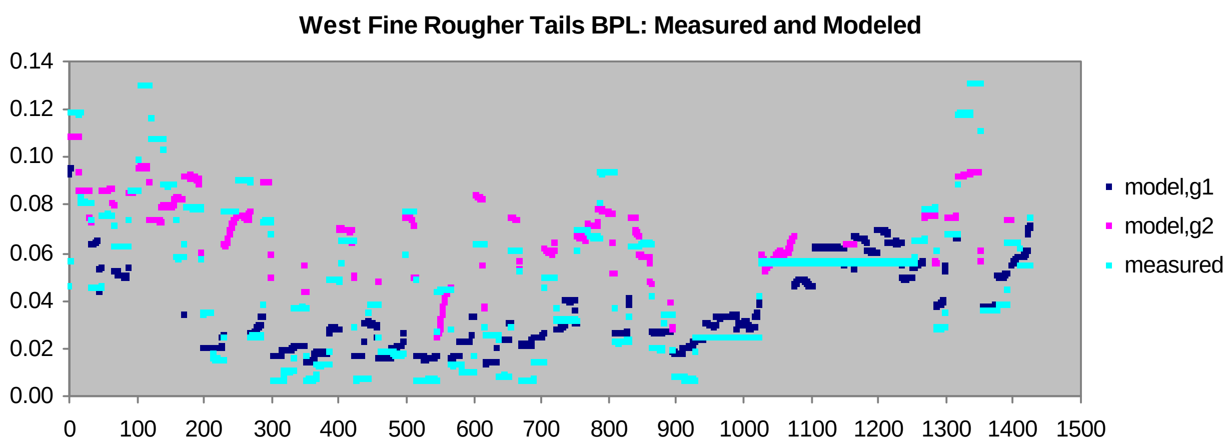

Figure 5. The Computer Modeling Approach Outlined in the Above Section Can Be Used to Simulate the Performance of the West Fine Rougher Circuit. Here, the Model Achieves a Correlation Coefficient of 0.9.

DIFFICULTIES IN MODELING DUE TO INADEQUACIES ASSOCIATED WITH THE PLANT DATA

As stated above, the Swift Creek plant, like most plants, is instrumented with the goal of providing human operators adequate information to control and monitor the plant. Thus, there are some inadequacies associated with the data with regard to developing a computer model of the plant, and ultimately an optimizing, adaptive control system. These inadequacies can be classified into five main categories: (1) limited amount of data, (2) noise in the data, (3) questions about data quality, (4) anomalous data, and (5) insufficient data tagging. These issues are discussed further below.

Limited Amounts of Data

First, there simply is not enough data currently collected at the plant for the modeling effort to be as successful as it might be. There are not enough measurements to calculate mass balance for any single process. Thus, process recovery (one of the key parameters to be modeled) cannot be calculated directly, rather it must be estimated using a rule-of-thumb relating input and output flow rates. Certainly, the modeling effort would be greatly enhanced if recovery information were taken in the plant.

Further, the BPL measurements are not made often enough on a single process to allow effective modeling; the NMR requires approximately five minutes of sampling time to get stable feed and tails BPL values for one rougher process. Since the NMR monitors four roughers, only three data points are generated per hour for each of the lines; even though mass flow and other values are available at far more frequent intervals.

The effective neural network models of plant operations typically consisted of at least eighteen empirical parameters. Thus, to fit one computer model at least six hours of data were required. Using so few data points to train the computer model promotes the “memorization” of the data. When the number of input parameters is approximately equal to the number of data points used in training, parameters exist which match the data almost perfectly. Since the real data has noise and unmeasured significant variables, the "real" parameters (the ones which best reflect true process operation) will not match the data nearly so well. This problem means in essence that the effective life-span of a neural network model of this plant is usually less than the six hours which is the minimum modeling period. To overcome this problem, computer models were continuously being trained in the control system. Although this approach is feasible and implementable, it requires increased computational power and dramatically complicates the computer software.

Noisy Data

The data acquired from plant sensors is quite noisy. There are a variety of causes of this, but there are two primary sources of noise. First, there is sampling error associated with the plant sensors. Second, the communication channels include some level of noise. The problem of noise in the data was addressed in this project, and ultimately it was effectively managed. However, this problem was never completely solved.

Data Quality

Some questions rose about the integrity, or at least the accuracy of the data. Data channels within the plant did not always carry “live” or real measurements. However, there is no time stamp associated with the data signals, nor is there any information indicating that the data value is in fact a measured value. For instances, when the operation of a given sensor is temporarily disrupted, the data acquisition system records a bogus value for that sensor. Sometimes this value is zero, other times it is an apparently random value.

This problem was addressed in the current system using a heuristic. The rule employed was to interpret unvarying values to be inaccurate measurements. This heuristic was deemed appropriate because the real-time data reporting would typically “hold” values in memory, and report them when queried. Unfortunately, the noise in the data transmission system makes it difficult to interpret the term "unvarying values." Interestingly enough, some of the data channels have a name suggesting the presence of a “data-is-good flag,” but none of these currently carry meaningful information.

Anomalous Data

A small percentage of the data recorded using the data acquisition system seemed to be contrary to what was known about the way in which the plant was operating. There was no way to efficiently recognize such anomalous data values. This complicates the modeling effort. Three examples follow. First, was a situation related to the NMR operation. Oftentimes, apparently-valid NMR readings would indicate for several hours smaller BPL values for a process feed stream than for the same process's tails stream. A second example involved the online-data-reporting system’s "engineering limit." This value for BPL was set to a value of feed BPL equal to 30. However, there were instances in which the NMR measured values considerably higher than 30. Third, a comparison of real-time data measurements with off-line laboratory analysis were at times irreconcilable.

Insufficient Data Tagging

The sequence of NMR analyses is generally the same (i.e., west fine feed, west fine tails, west course feed, etc.), but not always. The operator can change the sequence, or for a stream a bad reading could be taken, thus complicating the on-line control. And the NMR measurements as delivered through the real-time data system are contaminated by transmission noise. Thus, recognizing NMR measurement times and values can be difficult. Currently, the best solution to this problem requires human guidance and looking ahead at "future" measurements.

Summary

The effective operation of the optimizing, adaptive process control system generally depends heavily on accessibility to an accurate computer model of the system to be controlled. The most effective generic mechanism for modeling a system is a neural network. The neural network relies on having sufficient accurate data from the system on which to train. As with most real-time systems, the data acquisition system at the Swift Creek plant causes some problems when attempting to completely automate the process of modeling and controlling the plant. These problems have been identified in the current project, and, for the most part have been effectively dealt with. However, it is important to note that the problems with the available real-time data discussed in the preceding sections will be prominent in virtually all plants. Further, the problems associated with any particular data acquisition system will be plant-specific. Thus, the successful implementation of an adaptive control system will require an in-depth understanding of the data acquisition system being used.

RESULTS OF PLANT SIMULATIONS

A neural network model is at the heart of the optimizing, adaptive controller designed to manipulate the Swift Creek plant. This section describes the neural network model, and demonstrates its effectiveness.

OVERVIEW OF THE NEURAL NETWORK MODEL

Artificial neural networks are computational systems that mimic the biological neural networks of the mammalian brain. The human brain contains about 100 billion neurons (neural cells), interconnected in a complex network via synapses (a junction between axons and dendrites). Artificial neural networks are grossly simplified models of living neural systems.

A wide variety of neural network architectures (the arrangement and connection of neurons) have been used successfully to solve numerous problems. However, despite the differences in the architectures, neural networks are based on a common component, the neuron, which is the basic processor in neural networks. In their most basic form, neurons are computational units that receive multiple signals, sum these signals, and compute an output based on an activation function (generally nonlinear) that depends on the sum of the signals received. Each neuron has one output, which is generally related to the state of the neuron (its activation). The output of each individual neuron may well be passed on to other neurons in various positions in the network via weighted connections. Each neuron receives inputs over these connections, called synapses, from other neurons. The inputs are the activations of the incoming neurons multiplied by the weights of the synapses along which they travel. The activation of the neuron is computed by applying a threshold function to this product. A nonlinear threshold function is used to introduce nonlinearities into the neural network. An abstract model of the basic neuron is shown in Figure 6.

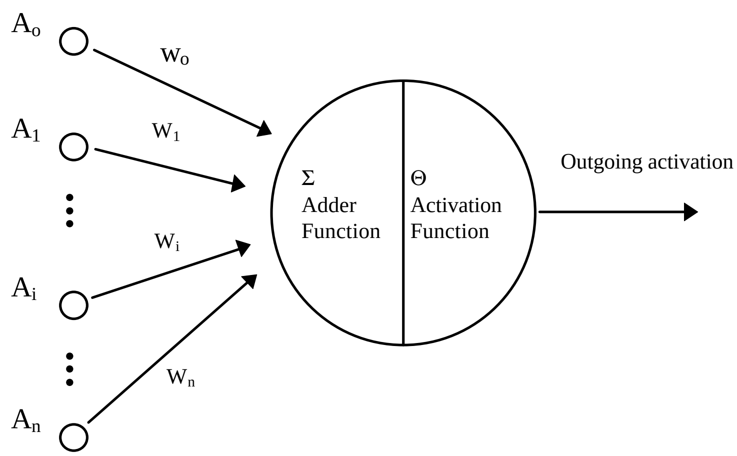

Figure 6. The Basic Neuron Receives Input in the Form of Activations from Other Neurons, Processes the Information, and Provides Its Own Outgoing Activation, Which Is Then Sent to Other Neurons in the Neural Network.

The activation or threshold function is generally a nonlinear function. Nonlinearity is an extremely important attribute to neural networks because it allows them to model the complex relationships existing between input and output parameters. The most commonly used nonlinear function that is appropriate for neural networks is the sigmoidal function defined by

$$f(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

where x is the sum of the input signals to the neuron.

The individual neurons of neural networks are placed in various layers. The neurons in the layers are interconnected by weighted synapses. Figure 7 shows a schematic of a typical backpropagation network consisting of three layers: (1) input layer, (2) hidden or middle layer, and (3) output layer. The input layer neurons receive an activation signal from the physical environment (data from the system to be modeled). These input layer neurons then sum the input signals and compute an activation based on their activation or sigmoidal functions. The resulting activation is passed to each of the neurons in the hidden layer (for a fully connected network each neuron in the input layer is connected to each neuron in the hidden layer, and each neuron in the hidden layer is connected to each neuron in the output layer). Along the way, the activation signals are multiplied by the weights associated with each of the synaptic connections along which the signals are passed. These weighted activation signals serve as inputs to the hidden layer neurons.

And, selecting the weights in the network such that it gives the correct answers is the whole problem.

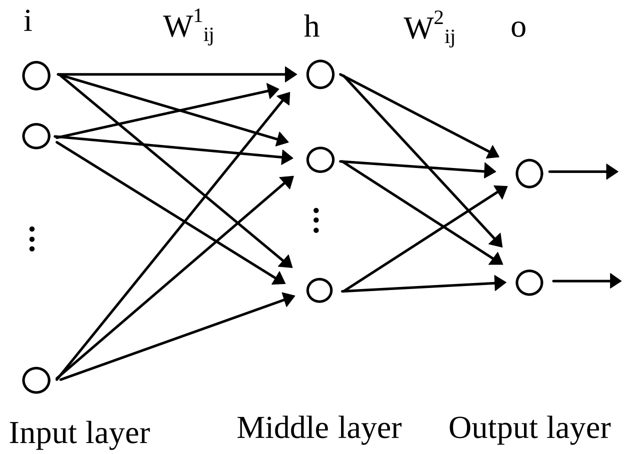

Figure 7. Typical Backpropagation Neural Networks Consist of Three Layers of Neurons Interconnected by Weighted Synapses.

The hidden layer neurons perform calculations with the signals similar to the calculations performed by the input layer neurons resulting in activation signals that are passed to the output layer neurons. The output neurons use these weighted input activation signals coming from the hidden layer neurons to compute their output activation signals. These activation signals coming from the output neurons are the output of the neural network. This process by which an input signal is received from the physical world, multiplied by weights associated with the connections between input and middle layer neurons, nonlinearized with activation functions, multiplied by a second set of weights associated with the connections between middle and output layers, and nonlinearized again with activation functions, is called a forward pass. This pass is used both in training a neural network and in using a trained neural network to model a system. It is, however, the backward pass which gives neural networks their adaptive capabilities. In the backward pass, the network weights are adjusted using a derivative-based algorithm so that the network accurately models the training sets it is presented.

As described above, neural networks have associated with them an architecture in which numerous neurons are connected into layers and a mechanism for accepting an input signal and converting said input signal into an output signal. The relationship between the network's output signal and its input signal is determined by the weighted connections which are adjusted in a backward propagation of errors. The backward propagation of errors through the network represents the training phase of a neural network while the forward pass is the actual implementation of the neural network. Generally, the implementation is easy and fast while the training can be complex and time-consuming.

Backpropagation neural networks take a training example (data from the system being modeled), compute an output signal, and then compute an associated error based on the appropriate known solution it is provided. Initially, its errors are due mainly to the fact that the weighting values on the synapses are not accurate. Thus, a mechanism is needed by which the weights can be adjusted in a manner so that the network "will get the correct answer." The backpropagation of errors is a relatively generic concept. There are many ways to do this. However, the classic backpropagation algorithm uses a derivative based approach.

Neural networks have the ability to learn any arbitrarily complex nonlinear mapping. This is due to the nonlinear activation functions and the introduction of a middle or hidden layer. However, there are potential drawbacks to neural networks. First, one of the most cited disadvantages of neural networks is that they can involve extremely long training times. Second, neural networks can "memorize" the training data but fail to extend generalizations to situations for which they have not been specifically trained. Often, this occurs when the neural network has too many hidden nodes; a delicate problem since too few hidden nodes and the neural network will not train while too many nodes causes the neural network to memorize. Third, neural networks do not give any indication as to why they do what they do. In other words, when a neural network is used as a computer model, it receives input data and produces an output value. There is no easy way of understanding the complex relationships between the input values and output values that are contained within the neural networks weight matrices. Thus, neural networks are the quintessential "black box" device.

NEURAL NETWORK PARTICULARS

The neural network software used in the current research effort was initially designed under a previous FIPR agreement with BCD Technologies. The computer software can be used to model a system about which the developer has no special knowledge. However, the more a model developer knows about the system being modeled, the more efficiently the model can be developed. Additionally, there are some decisions that must be made in implementing a neural network, and an experienced neural network practitioner will generally make these decisions more efficiently than a novice. These decisions include: (1) how many neurons to put in the middle layer, (2) what kind of learning rate to employ, (3) whether or not to include momentum terms which allow the system to overcome local optima, and (4) what kind of activation function to use.

The neural network computer model of the Swift Creek Mine was used to simulate the tails BPL in the system; this was the value that proved to be the most important, unmeasured parameter with regard to controlling the plant. The neural network model had available to it up to twenty-five different input parameters appearing in the database of the data acquisition system. Of these twenty-five, the neural network was programmed to be flexible in its choice of parameters to consider. It used the minimum required number to accurately model the plant operation. The neural network model had twenty hidden nodes, a single output node, used a learning rate of 2% and included a momentum term.

NEURAL NETWORK MODEL PERFORMANCE

The neural network model of the Swift Creek plant operation was trained using six hours of plant operating data, ran for 1000 epochs, and took approximately 20 minutes to train. The model performed acceptably both on training data and on test data. Its ability to accurately simulate test data demonstrates its ability to simulate the performance of future plant operations. Figure 8 shows how well the neural network model was able to project the operation of the plant. This figure compares the actual plant tails BPL to the plant tails BPL as predicted (or simulated) by the neural network model.

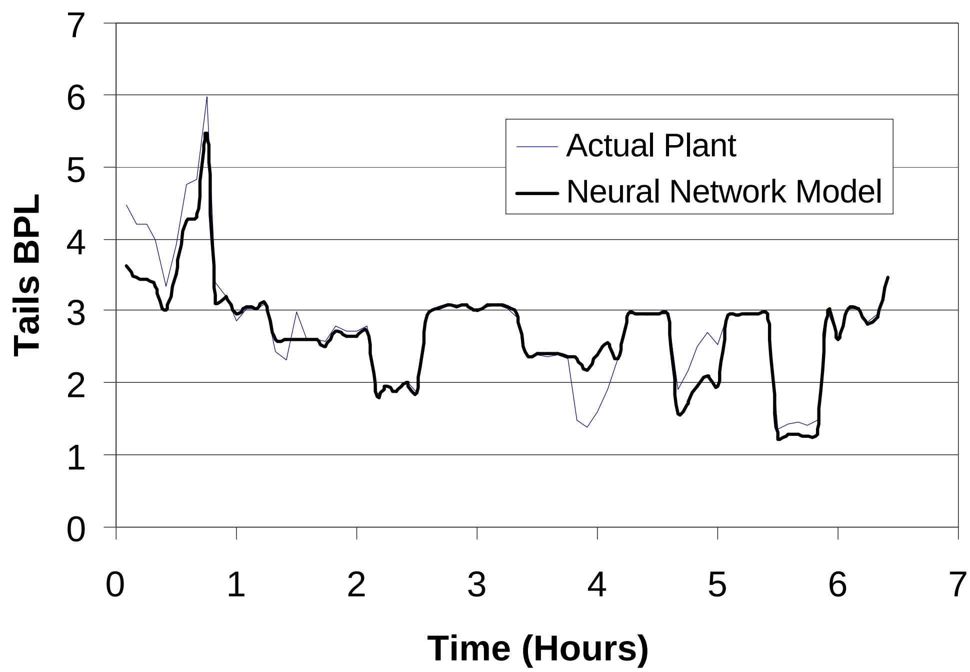

Figure 8. The Neural Network Model Is Able to Accurately Simulate the Operation of the Plant for the Six and One-half Hour Period Shown in the Figure Above. This Ability to Mimic the Operation of the Plant Is Critical in the Optimizing, Adaptive Controller Described in the Following Section.

The ability of the neural network simulation to accurately mimic the performance of the plant is extremely important for two reasons. First, as described earlier, the adaptive control system relies heavily on the simulation. The control system relies on the simulation at it considers alternative control strategies. Without an accurate simulation of the plant, these adaptive capabilities would be ineffective. Second, the neural network simulation is used to demonstrate the effectiveness of the control system since the controller was not tested on the actual plant.

AN OPTIMIZING, ADAPTIVE CONTROL SYSTEM

The three-tiered architecture used in the current project to achieve optimizing, adaptive process control results in a flexible system that performs well on the processing plant at Swift Creek Mine. As described in a previous section, the system employs a control element to manipulate the phosphate flotation plant, an analysis element to determine when and by how much unmeasured system parameters within the plant change, and a learning element to adjust the control element in response to the unmeasured parameters. This controller architecture proves to be effective in the current application, and is designed to be extensible to a variety of phosphate plants. Although in principle, the system could be developed almost in a generic sense (so that little to no adjustments would be needed to implement the system in any plant), in reality the particulars of the control system depend heavily on the sensors available within the phosphate plant being controlled. The issue of data acquisition is actually terribly important, and is considered in detail in the following section.

Testing the adaptive control system was a little problematic in that it could not be tested on the actual plant. However, the control system was adequately tested when it was used to manipulate a neural network simulation of the real plant. The neural network on which the control system was tested is the same neural network simulation described in the previous section. Figure 9 shows the time-history of the actual plant compared to the performance of the adaptive control system manipulating a simulation of the actual plant. The recovery values shown in Figure 9, and in subsequent figures, are scaled numbers so the actual plant recovery cannot be determined from this report. Notice that at times the control system is producing a higher recovery than was achieved in the actual plant for the same conditions. At times, the adaptive controller system is not performing as well as the human operator. Basically, the adaptive controller is using a different strategy than the human operator. This point is reinforced by Figure 10 that shows fatty acid usage for the two scenarios of Figure 9. Here, again, the human operator and the adaptive controller make similar decisions.

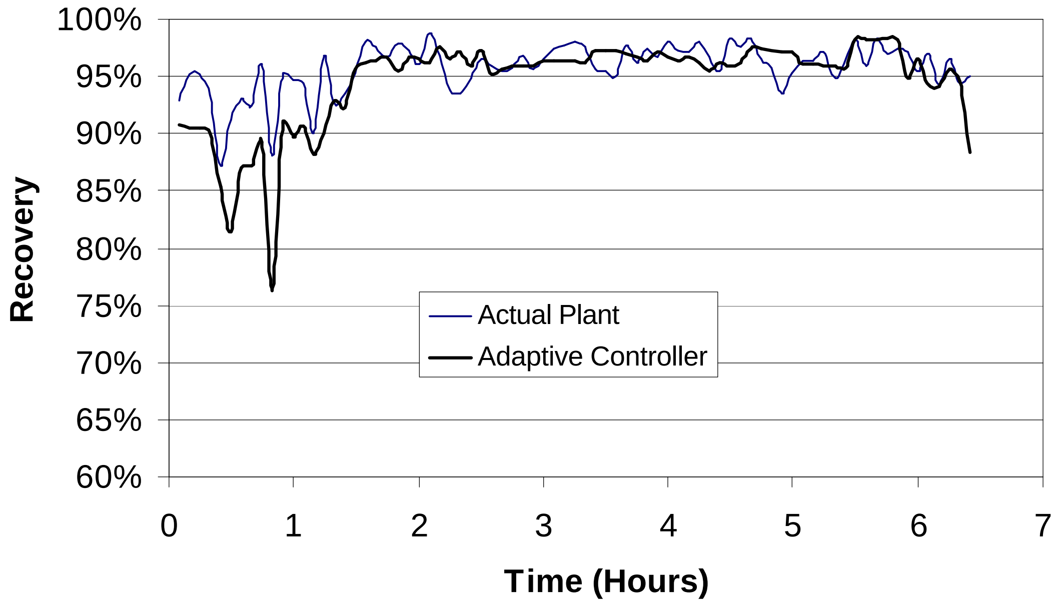

Figure 9. The Plot Above Compares the Recovery Actually Achieved in the Plant to the Recovery Achieved Via the Adaptive Controller Manipulating a Simulation of the Plant, Both Over a Six and One-half Hour Time Period. Here, the Adaptive Controller Does Better Than the Human Operator at Times, and at Times Does Worse than the Human Operator.

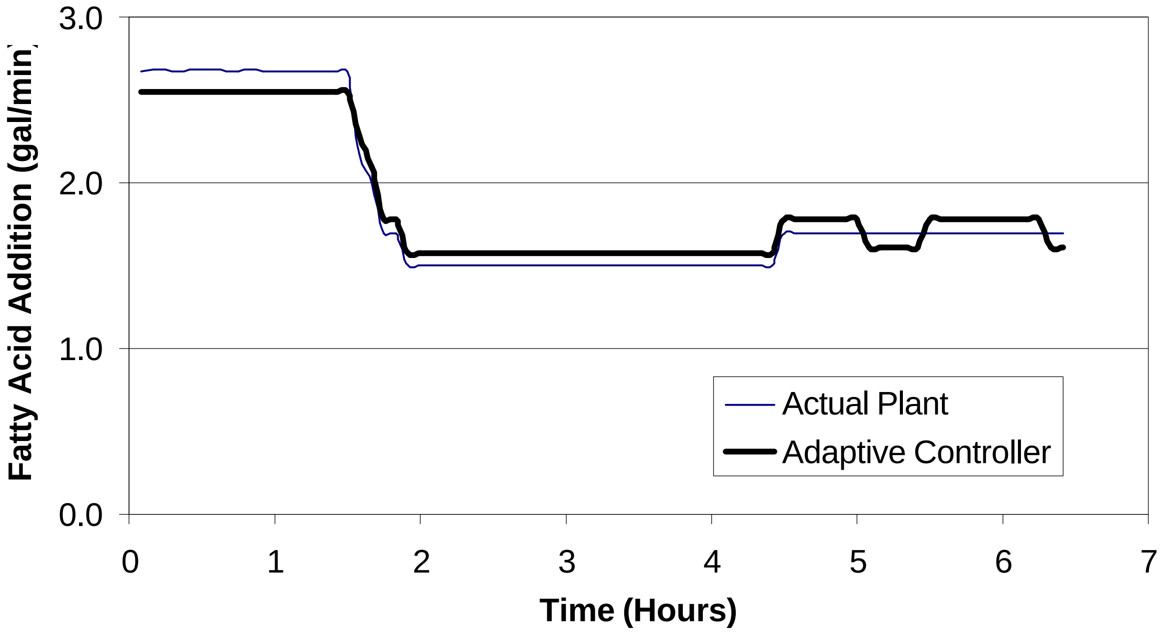

Figure 10. Notice in the Above Figure that the Fatty Acid Addition Indicates That the Adaptive Controller Is Employing a Strategy for Controlling the Plant That Closely Resembles the Strategy of the Human Operators.

The above two figures give an indication that the adaptive control system is controlling the plant reasonably well. However, some statistics gleaned from extended periods of operation prove to be even more convincing. For example, over a 24-hour period, the actual plant average recovery was 95.8% and the average fatty acid addition was1.86 gal/min. During that same 24-hour period (i.e., the same operating conditions were simulated), the optimizing, adaptive control system produced an average recovery of 94.6%, and an average fatty acid addition of 1.86 gal/min. Thus, the adaptive control system performed at approximately the same level of the human operator.

At first consideration, the fact that the adaptive control system did not out-perform human operators might seem to be disappointing. However, there are at least two important reasons why this might be true. First, the human operator is able to consider sensory information that is not available to the computer control system. For instance, the plant operator is able to walk out into the plant and get feedback as to how well the plant is performing. This can be achieved simply by looking at a handful of tails, by listening to the sound of the plant, and in numerous other ways. This feedback serves as important information as the operator manipulates the systems in the plant. Second, the human operator is generally performing based on years of experience with working in the plant. The adaptive control system, although able to make short-term decisions remarkably fast, suffers from a lack of long-term experience or tuning.

In summary, the optimizing, adaptive control system performs approximately at the level of human operators who currently control the plant. Although the computer control system could potentially be improved with: (1) the incorporation of more accurate neural networks, (2) better noise filtering on the sensors, (3) more consistent (less ambiguous) data, and (4) a variety of other things, it might well be that the controller is not going to consistently outperform the human operators. This is likely a consequence of the fact that the human operators rely on sensory information simply not available to the computer controller, and to the fact that the operators at the Swift Creek plant are doing quite well. This plant is already operating at near-peak conditions, running on high-quality feed. Although it could not be done in the current study, it would be interesting to evaluate the performance of the adaptive controller in a less efficient plant.

AN ALTERNATIVE APPROACH TO PLANT CONTROL

During the process of designing, implementing, and testing the optimizing, adaptive control system, a large amount of plant data was collected and analyzed. During this analysis process, some relationships were observed and validated that can potentially be used as a simple alternative to the complex optimizing controller discussed previously in this report. Preliminary results indicate that this approach will be an effective mechanism of controlling processing plants.

Phosphate processing plants tend to have numerous sub-systems, each of which can be quite complex in their own right. However, fundamentally, the main decision that can generally be made to control the plant is fatty acid addition. And, the appropriate amount of fatty acid addition is generally dependent on the quality and amount of feed coming into the plant. This fundamental relationship is born out in the data analyzed during the design of the adaptive control system. An attempt has been made to quantify this relationship, and to suggest a way to utilize this information to control the plant.

The plant at Swift Creek operates very smoothly and the operators often leave the fatty acid feed rate the same for considerable periods of time. Analysis of several thousand data points where feed BPL, pumping rate, tails, and fatty acid setting were correlated, show that there is a definite relationship that can be used to predict the fatty acid requirements needed to obtain high recoveries. Appendix A shows a series of calculations for feed BPL covering the range obtained from actual plant data. Figure 11 shows a typical plot one can obtain showing that the amount of fatty acid required to obtain greater than 90 pct recovery changes dramatically as the amount of BPL in the system changes. Figure 12 is a similar plot for just higher grade feed. As can be seen the curves that can be drawn through the points of the graphs provide an operating line that can be used to control the plant.

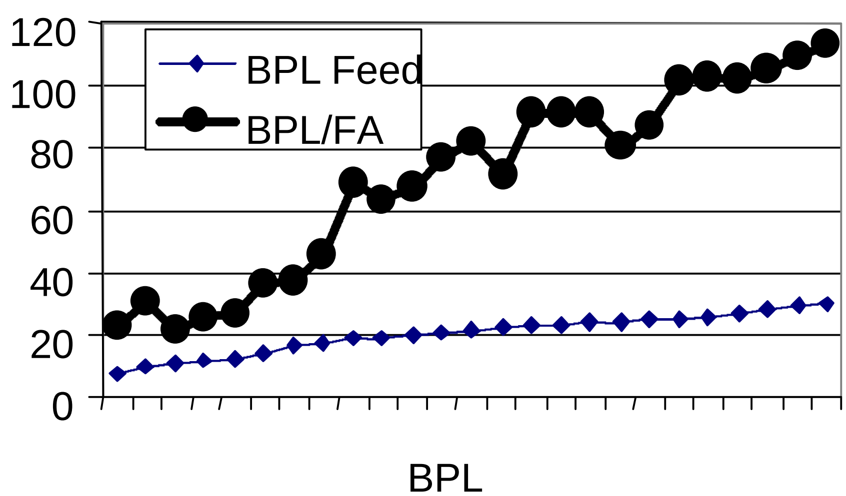

Figure 11. The Relationship between BPL of the Feed and the Amount of Fatty Acid Required for a Range of 7.4 to 29.4 Percent BPL.

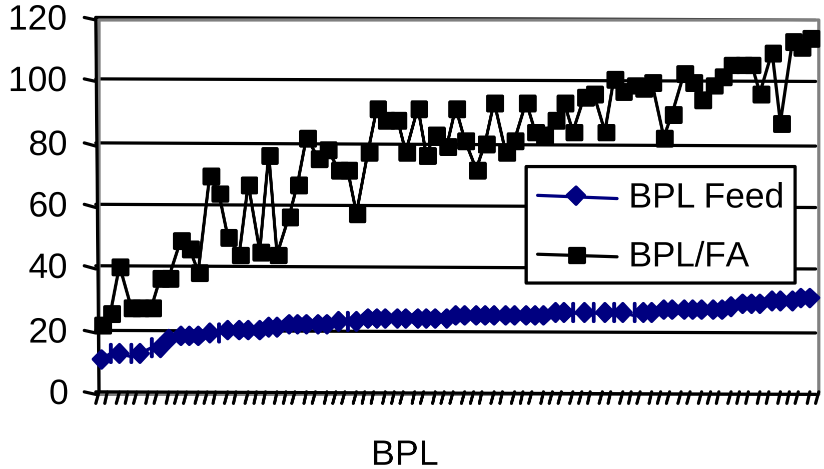

Figure 12. The Figure Above Shows the Relationship between BPL of the Feed and the Amount of Fatty Acid Required for a Range of 10.3 to 29.8 Percent BPL.

Another data set was acquired and archived during a period in which the plant was operating efficiently. The recovery of the plant during the time in question is shown in Figure 13. Here it can be seen that during the eighty-minute interval, the plant recovery transitions from values of approximately 88% to values that are consistently above 94%. The feeling is that during this period the plant operators are performing at a high level of efficiency. Thus, the goal is to capture the operators' knowledge and to archive it so that it can be used consistently.

This knowledge is represented in Figure 14 which shows a plot of the Feed BPL-to-fatty acid addition over the given time period. Notice that although this plot has some oscillations, it can be represented by a linear relationship (at least in various regions). This curve (or these curves) can be used to compute an effective, if not optimum fatty acid addition. The user can select the correct value of BPL on the x-axis, read up to the curve, and then compute the fatty acid addition. Based upon the above calculations, other data points that were not used before were evaluated and it was found that the BPL/FA were quite similar, usually falling within 5 percent of previous values. This approach could be used in virtually any plant where the plant is running efficiently, i.e., in a stable mode.

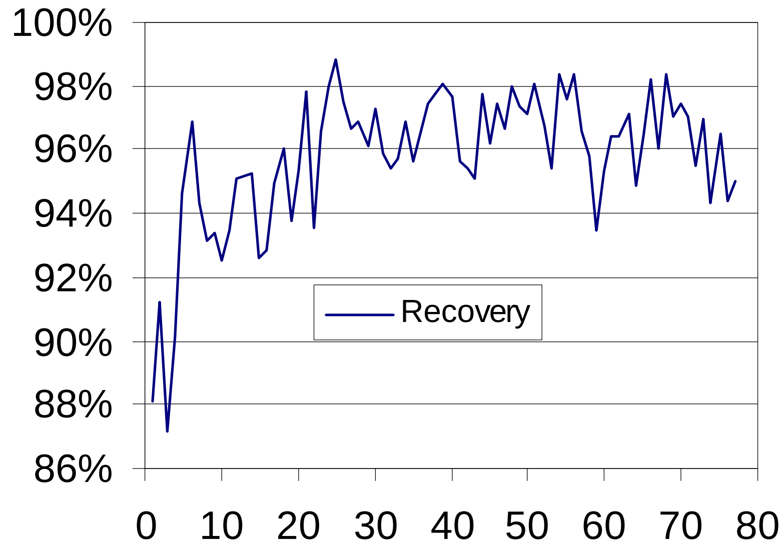

Figure 13. The Plant Is Obviously Operating Efficiently During the Time Period Shown. During this Time of Efficient Performance, the Operators Are Making Effective Decisions.

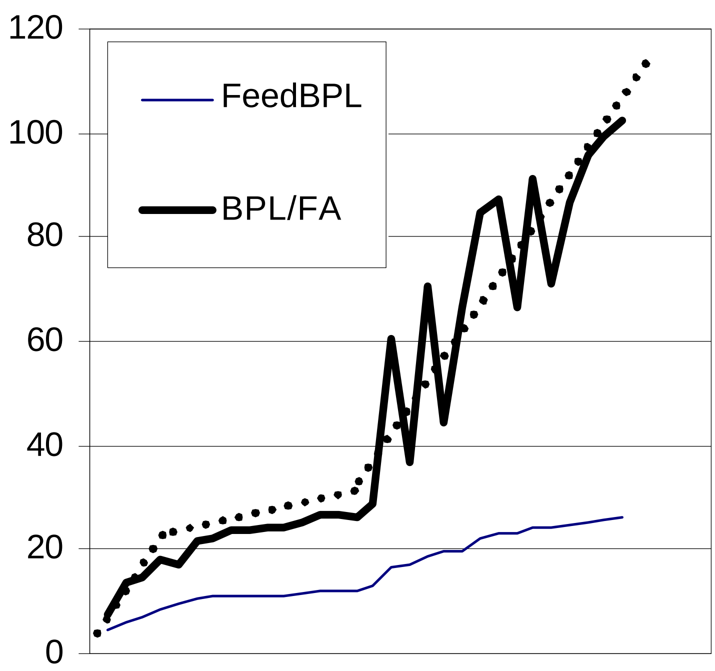

Figure 14. The Above Figure Shows a Plot of Feed BPL-to-Fatty Acid Addition. The Dotted Lines in the Above Plot Can Potentially Be Used to Control the Plant.

SUMMARY AND CONCLUSIONS

A level-2 intelligent controller consisting of three primary elements has been developed, implemented, and tested in a phosphate processing plant. The primary elements of the control system are: (1) the control element, (2) the adaptive element, and (3) the learning element. These three elements combine to provide efficient, robust control of the plant. In simulations, the optimizing, adaptive control system performed as well as human operators in a plant operating at near-peak levels.

The optimizing, adaptive control system is effective, and can in general be applied to any phosphate processing plant. However, there are some issues that must be addressed before this approach is adopted at an operating plant. First, the plant must be adequately instrumented. Even though the Swift Creek plant is well instrumented by industry standards, there was still a large amount of information (of the type the operators could estimate) that would be beneficial to controlling the plant. Second, there are a variety of issues associated with the data acquisition system that should be in place. There is a large amount of pre-processing of the data that is necessary to successfully implement any adaptive control system. Finally, the maintainability of the control system must be considered. The software necessary to implement the ideas discussed in this report is necessarily complex. To keep the system operating, the plant would require a full-time computer engineer to ensure that the system continued to operate per its design specifications. Obviously, this can prove to be expensive. Human operators actually control complex processing plants quite effectively. There are many reasons for this including invaluable experience gained over years of practice, their ability to recognize subtle but powerful relationships between various parameters, and the fact that the effective manipulation of these plants does not require split-second decision-making.

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APPENDIX A – FEED BPL, FATTY ACID, AND RECOVERY DATA

FeedBPL	FeedTPH	FA	TailsBPL	Recovery	BFL/FA
0.21	495.03	1.69	1.19		
0.95	498.47	1.69	2.66		
1.79	538.09	1.69	2.08	23.1	5.7
2.07	494.91	1.69	1.19	61.5	6.06
2.35	540.04	1.69	3.09	11.9	7.51
2.46	541.74	1.69	2.08	43.4	7.89
2.59	543.90	1.69	2.86	26	8.34
3.30	497.01	1.69	1.14	74.5	8.82
3.91	519.31	1.69	1.39	76.2	12.02
4.39	455.85	2.68	1.57	76	7.49
4.91	501.90	1.69	1.60	78.2	14.58
5.06	507.69	1.69	1.78	76.4	15.2
5.57	529.93	1.69	1.34	79.8	13.92
6.24	503.16	1.69	1.44	84.5	18.56
6.27	576.96	2.68	1.66	82.3	13.55
6.32	549.12	1.69	2.03	78.5	20.53
6.35	523.03	1.69	2.40	74.7	19.65
6.39	537.16	1.69	2.82	70.4	20.31
6.60	555.03	1.69	1.45	85.3	21.67
6.75	561.70	1.69	1.40	86.1	22.43
6.86	576.83	2.68	2.64	74.3	14.84
7.06	514.09	1.69	1.90	82.1	21.47
7.23	551.07	1.69	1.53	85.8	23.57
7.28	535.16	1.69	1.95	82.1	23.05
7.43	514.69	1.69	1.23	88.9	22.62
7.46	518.27	1.69	2.60	76.6	22.88
8.64	561.29	2.68	2.57	80.1	18.16
9.30	518.53	1.69	1.89	86.4	28.53
9.64	474.57	2.67	1.55	89.2	17.13
9.89	525.71	1.69	1.49	89.9	30.76
10.06	530.47	1.69	2.96	80.3	31.58
10.33	573.70	1.69	1.66	89.2	55.07
10.37	561.92	2.68	0.97	93.7	21.82
10.86	542.80	2.67	1.84	88.6	22.08
10.89	579.26	2.68	2.25	86.2	23.62
11.17	573.58	2.67	2.21	86.7	24
11.19	579.75	2.67	2.51	85	24.3
11.30	573.69	2.68	2.22	86.8	24.28
11.84	572.10	2.67	1.74	90.2	25.37
12.05	562.41	1.69	0.81	95.1	40.1
12.17	587.10	2.68	1.75	90.4	26.76
12.20	587.10	2.68	1.74	90.4	26.83
12.24	571.57	2.68	2.70	85.2	26.2
13.19	579.14	2.67	2.83	85.6	28.61
14.05	517.12	2.68	1.24	94.1	27.21
14.05	566.62	2.20	0.76	96.4	36.18
14.79	561.37	2.67	3.85	82.6	31.1
15.60	581.91	2.68	2.75	88.2	34

FeedBPL	FeedTPH	FA	TailsBPL	Recovery	BFL/FA
15.97	580.69	2.68	2.45	89.7	34.73
16.57	547.76	1.50	2.52	89.8	60.5
16.92	581.65	2.68	2.00	92.1	36.86
16.92	575.10	2.68	2.86	88.7	41.56
17.14	570.88	2.68	3.74	85.4	36.65
17.27	543.58	1.69	2.96	88.5	55.55
17.40	552.42	1.69	3.40	86.9	56.85
17.65	485.91	1.69	1.59	94	50.75
17.65	558.59	2.20	2.59	90.2	48.82
17.78	567.42	2.20	0.97	96.3	45.86
17.88	567.99	1.69	3.01	88.7	60.09
18.01	571.40	2.68	2.60	90.3	38.54
18.73	623.48	1.69	1.73	93.8	69.1
18.78	564.79	1.50	3.50	87.5	70.7
19.03	581.39	2.67	3.18	88.8	41.34
19.04	556.83	2.68	3.11	89.1	39.68
19.20	557.13	1.69	1.69	94.1	63.3
19.41	563.32	2.20	2.26	92.4	49.68
19.61	605.98	2.68	2.74	90.6	44.5
19.65	579.38	2.20	3.24	89	51.73
19.75	573.98	1.70	1.28	95.7	66.68
20.09	589.63	2.67	3.31	89	44.37
20.12	592.82	2.68	2.90	90.3	44.67
20.38	557.81	1.50	2.50	91.6	75.79
20.45	579.52	2.68	2.99	90.2	44.49
21.11	587.44	2.20	1.76	94.4	56.36
21.13	533.98	1.69	1.02	96.8	66.75
21.44	570.34	1.50	1.67	94.8	81.52
21.53	585.22	1.69	2.24	93	74.62
21.80	533.78	1.50	2.15	94.3	77.57
22.18	603.40	1.89	1.70	94.9	71.19
22.31	570.84	1.50	4.31	. 87.1	84.9
22.34	590.88	2.20	3.73	88.8	60
22.56	532.24	1.69	2.32	93.1	71.05
22.85	603.01	2.67	4.22	87.6	51.61
22.95	544.49	2.20	2.76	91.9	56.82
23.07	565.18	1.69	2.45	92.7	77.15
23.08	591.41	1.50	1.85	95.6	91
23.14	209.75	1.50	1.99	94.3	32.36
23.18	565.14	1.50	2.36	93.2	87.3
23.34	558.89	1.50	3.19	90.8	86.98
23.41	555.37	1.69	3.27	90.6	76.93
23.41	614.24	2.17	1.40	96	66.26
23.53	582.45	1.50	1.41	96	91.37
23.56	545.81	1.69	2.95	91.6	76.09
23.89	655.72	1.88	1.26	96.5	82.79
23.90	556.58	1.69	1.82	94.9	78.7
23.99	570.08	1.50	0.85	97.3	91.17
24.01	592.23	2.68	5.24	85.4	53.25
24.14	562.49	1.69	2.09	94.2	80.35
24.15	587.32	2.00	1.78	95	70.92

FeedBPL	FeedTPH	FA	TailsBPL	Recovery	BFL/FA
24.18	557.87	1.69	1.20	96.7	79.82
24.22	582.00	2.20	4.17	88.5	88.5
24.22	576.16	1.50	2.76	92.4	93.03
24.30	535.45	1.69	1.20	96.7	76.99
24.31	568.87	1.69	3.74	89.7	81.83
24.32	560.32	1.69	2.92	92	80.63
24.40	694.73	1.88	2.63	92.8	90.16
24.44	538.91	1.69	4.79	86.9	77.93
24.69	567.93	1.69	3.33	91	82.97
24.70	565.10	1.69	2.19	94.1	82.59
24.86	593.33	1.70	2.47	94.3	86.76
24.91	627.30	1.69	2.58	93.1	92.46
25.05	559.91	1.69	2.70	92.8	82.99
25.06	567.67	1.50	2.51	93.3	94.84
25.07	573.63	1.50	2.36	93.7	95.87
25.09	559.91	1.69	2.71	92.6	.83.12
25.09	678.34	1.69	1.76	95.3	100.71
25.42	567.18	1.50	2.37	93.8	96.12
25.52	579.61	1.50	3.33	91.3	98.61
25.59	570.81	1.50	3.28	91.4	97.38
25.64	582.40	1.50	2.97	92.2	99.55
25.79	534.95	1.69	1.86	95.2	81.63
25.93	577.70	1.69	1.42	96.3	88.64
26.03	591.08	1.50	2.13	94.5	102.57
26.20	569.63	1.50	1.85	95.3	99.49
26.26	536.73	1.50	3.60	90.8	93.93
26.35	558.68	1.50	1.79	95.4	98.14
26.55	572.77	1.50	1.57	96	101.38
26.56	616.26	2.20	7.76	81.4	81.4
27.33	575.19	1.50	2.86	93	104.8
27.51	656.36	2.20	8.98	78.1	82.09
27.94	568.14	1.50	1.62	96.1	105.43
27.99	561.86	1.50	2.18	94.8	104.84
28.09	638.11	1.88	3.80	90.9	95.35
28.74	569.54	1.50	1.96	95.4	109.13
29.11	556.10	1.88	3.54	91.9	86.11
29.45	575.09	1.50	3.85	91.2	112.9
29.66	562.01	1.50	4.08	90.8	110.9
29.85	571.55	1.50	4.41	90.1	113.74