Improved Fuzzy Control Through the Inference of Difficult to Measure Parameters

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Abstract—Researchers at the U.S. Bureau of Mines have developed an innovative approach to process control that combines the control capabilities of fuzzy logic, the search capabilities of genetic algorithms, and the modeling capabilities of neural networks. One of the key aspects of this approach to process control is the use of a neural network model to infer information from the physical system that is difficult or expensive to measure directly with sensors. Often this unmeasured information is critical to successful control of the system. The unmeasured system information can be inferred by employing the search capabilities of genetic algorithms. In the approach presented, a genetic algorithm is used in conjunction with a neural network model of a physical system and sensory information that is available to obtain needed information that cannot be measured directly. The effectiveness of this approach is demonstrated on a specific system from the mineral processing industry, a hydrocyclone separating device that is used to achieve physical separation of mineral samples.

I. INTRODUCTION

The development of powerful techniques from the field of artificial intelligence has dramatically improved scientist’s ability to develop computer models, to design equipment, and to produce process control systems. Three such techniques, neural networks, fuzzy logic, and genetic algorithms, have been especially popular and useful tools in attempts to produce intelligent, adaptive computer systems. Neural networks have been used effectively in both the development of computer models and process control systems [1]. Fuzzy logic has proven to be an effective aid in the production of process control systems [2], and especially in the formation of adaptive process control systems [3]. Genetic algorithms have been used in a number of learning systems [4]. Researchers at the U.S. Bureau of Mines have developed an approach to adaptive, intelligent computer systems that combines the capabilities of each of these three techniques [5]. This approach, which has been applied in a number of engineering problems, is especially inviting because it allows for the inference of values of important control parameters that are not measured directly.

The ability to discern the values of system parameters that are not measured directly is especially important in the minerals industry. The minerals industry has a number of situations in which it is impractical to fully instrument processing systems [6]. Generally, it is too expensive, too dangerous, too time-consuming, or the appropriate sensors are not available to allow for accurate measuring of system parameters. Unfortunately, the efficient manipulation of these systems often depends on knowledge of the unmeasured system parameters. Thus, the ability to determine the value of unmeasured system parameters without directly measuring them is important to establishing optimal control. Such an approach for discerning system values has been included in the adaptive control system developed at the U.S. Bureau of Mines [5].

This paper describes an approach for determining the values of system parameters that are not directly measured. The approach boils down to using a genetic algorithm to solve a curve fitting problem. The genetic algorithm for solving a curve fitting problem. The genetic algorithm relies on a neural network model of the physical system, and plays an integral role in an adaptive fuzzy logic process control system. The effectiveness of the approach is demonstrated using a specific system from the mineral processing industry, a hydrocyclone separating device that is used to achieve physical separation of mineral samples.

II. ARCHITECTURE FOR ADAPTIVE PROCESS CONTROL

Fig. 1 shows a schematic of the Bureau’s adaptive process control system. The heart of this control system is the loop consisting of the control element and the problem environment. The control element is composed of a fuzzy logic controller, and receives information from sensors in the problem environment concerning the status of the condition variables. It then computes a desirable state for a set of action variables. These changes in the action variables force the problem environment toward a pre-defined 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. However, the mechanics of a fuzzy logic controller makes it possible to adapt a control strategy in real time.

The adaptive capabilities of the system shown in Fig. 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 an alteration to a parameter that is not
included explicitly in the fuzzy logic controller. (Of importance is the fact that the change affects the response of the problem environment, otherwise it has no effect on the way in which the control element must act to efficiently manipulate the problem environment.) 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.

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 Fig. 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 developed by the U.S. Bureau of Mines is provided below.

The control element is composed of a fuzzy logic controller. Fuzzy logic controllers are rule-based systems that mimic the "rule-of-thumb" approach used by humans in decision-making. The uncertainty associated with human decision-making is incorporated into fuzzy logic controllers via the use of abstract concepts represented with linguistic variables. The fuzzy linguistic variables are defined using fuzzy membership functions, and an entire theory has been developed to process the abstract knowledge [7].

The analysis element is charged with the task of recognizing changes in parameters associated with the problem environment not taken into account by the rules used in the control element. Changes to any of these parameters can dramatically alter the way in which the system responds to external stimuli, thus forming a new problem environment requiring an altered control strategy. 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 computer model of the physical system. 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 data base or a computer model. Storing such an extensive data base can be cumbersome and requires extensive computer memory. Therefore, using a computer model is more robust and efficient. Since this approach is used in association with a number of different physical systems, the robust nature of a neural network makes it quite inviting as a modelling tool. In the approach adopted here, the neural network computer model predicts the response of the physical system. This predicted response is compared to the actual response of the physical system. When the two responses differ by a threshold amount over a finite period of time, the physical system is considered to have been altered.

When the above approach is adopted, the problem of computing the new system parameters becomes a curve fitting problem [8]. 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 has been forged in which a genetic algorithm is used to compute the values of the parameters associated with a physical system. This approach allows for the computation of variable values that are not directly measured in the physical system. Thus, the neural network model and a genetic algorithm can be used to overcome a lack of sensory information.

A learning element must adapt the control strategy implemented by the control element, based on the changes quantified by the analysis element. This adaptation is effectively accomplished by allowing a genetic algorithm to alter the membership functions associated with the fuzzy logic controller that composes the control element. Details of the implementation can be found in Karr and Gentry [3].
III. HYDROCYCLONE SEPARATOR

The use of hydrocyclones is the standard method of classifying slurries in the mineral processing industry. Hydrocyclones are continuously operating separating devices that utilize centrifugal forces to accelerate the settling rate of particles. They have achieved such wide popularity because of their simplicity, their durability, and their relatively low cost. Hydrocyclones are now used increasingly in closed-circuit grinding, de-sliming circuits, de-gritting procedures, and thickening operations [9].

A typical hydrocyclone is shown in Fig. 2. The lower portion of a hydrocyclone is a conical vessel with an opening at the apex or bottom to allow for the removal of the coarse or heavier particles. The conical section is joined to a cylindrical section, the top of which is closed with the exception of an overflow pipe known as a vortex finder. The vortex finder prevents the tangentially fed mineral from going directly into the overflow, while allowing the fine particles a means of exiting the hydrocyclone. In this cylindrical section the actual separation occurs, due to the existence of a complex velocity distribution which carries the coarse particles to the apex and the fine particles out the top.

Hydrocyclones have traditionally been modeled using empirical relationships. Plitt [10] identified a model that is still used extensively today to predict the $d_{50}$ or split size. The split size is that size particle (given by diameter of the particle) that has an equal chance of exiting the hydrocyclone either through the underflow or the overflow, and is often used to quantify a separation process. Unfortunately, this particular model does not perform well across a spectrum of hydrocyclone sizes. Therefore, a traditional backpropagation neural network model of a hydrocyclone has been developed, and has been incorporated into a process control system for hydrocyclone separations. The hydrocyclone model is a three layer, backpropagation neural network. The neural network has eight input nodes, eleven hidden nodes, and one output node. The inputs to the neural network model are: the diameter of the hydrocyclone, $D_o$, the diameter of the slurry input, $D_i$, the diameter of the overflow, $D_o$, the diameter of the underflow, $D_u$, the height of the hydrocyclone, $h$, the volumetric flow rate into the hydrocyclone, $Q$, the percent solids, $\phi$, and the density of the solids, $\rho$. The output of the neural network model is the $d_{50}$ size. A schematic of the neural network is shown in Fig. 3.

Fig. 2. A typical hydrocyclone.

Fig. 3. Schematic of the hydrocyclone neural network model.

Fig. 4. Performance of a neural network model of a hydrocyclone.
hydrocyclone neural network model appears in Fig. 3. Fig. 4 shows the performance of the neural network model on both training and test data. The model predicted \( d_{50} \) is plotted against a value obtained from physical experimentation.

The neural network model plays an integral role in the adaptive control scheme. The values of the percent solids and the density of the solids are quite important in the control scheme used to manipulate a hydrocyclone system. However, these values are both inconvenient and expensive to measure. Therefore, \( \phi \) and \( \rho \) are rarely measured in industrial settings. The neural network model can be used in conjunction with a genetic algorithm to determine the unmeasured values of \( \phi \) and \( \rho \). The genetic algorithm is supplied with information concerning the values of all of the measured parameters \( (D_c, D_i, D_o, h, \text{ and } Q) \), the associated \( d_{50} \) size, and access to the neural network model. The genetic algorithm (using concatenated binary linearly mapped string representation) then searches for the values of \( \phi \) and \( \rho \) that, according to the neural network model, elicits the measured \( d_{50} \). In a number of test cases, the genetic algorithm determined values that were within 3.5\% of the actual measured values.

An inviting aspect of this approach is that it is not limited to determining the value of only two input parameters. In fact, for the hydrocyclone, the approach has been extended to the third input parameter that is often unmeasured, \( Q \). This particular problem of inferring three input parameters, although not as common as the situation mentioned above, has been solved using a genetic algorithm. In all test cases, the genetic algorithm found values that were within 4.2\% of the actual measured values.

Currently, the above approach is being implemented in a control system for a hydrocyclone. The adaptive control system is being developed as part of an ongoing research project at the U.S. Bureau of Mines, Tuscaloosa Research Center. The completed control system is scheduled to be installed in an industrial plant by the end of 1994.

IV. SUMMARY

A procedure for inferring difficult to measure parameters in industrial systems has been presented. The method relies on the use of a neural network model of the physical system and a genetic algorithm. This procedure can be incorporated into a complex adaptive process control system based on fuzzy logic developed by researchers at the U.S. Bureau of Mines. The effectiveness of the approach has been demonstrated on a system from the field of mineral processing, a hydrocyclone separating device that is used to achieve physical separation.

REFERENCES