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A RECONFIGURABLE STRATEGY FOR DISTRIBUTED DIGITAL PROCESS CONTROL‡

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ABSTRACT

A reconfigurable control scheme is proposed which, unlike a preprogrammed one, uses stochastic automata to learn the current operating status of the environment (i.e., the plant, controller, and communication network) by dynamically monitoring the system performance and then switching to the appropriate controller on the basis of these observations. The potential applicability of this reconfigurable control scheme to electric power plants is being investigated. The plant under consideration is the Experimental Breeder Reactor (EBR-II) at the Argonne National Laboratory site in Idaho. The distributed control system is emulated on a ring network where the individual subsystems are hosted as follows: (i) the reconfigurable control modules are located in one of the network modules called *Multifunction Controller*; (ii) the learning modules are resident in a VAX 11/785 mainframe computer; and (iii) a detailed model of the plant under control is executed in the same mainframe. This configuration is a true representation of the network-based control system in the sense that it operates in real time and is capable of interacting with the actual plant.

1. INTRODUCTION

Complex processes require integration of a large number of subsystem and controller modules. This results in complex large-scale design, operation, and maintenance problems. In a dynamic system with widely varying operating conditions, the control and decision functions need to be reconfigured during plant operations over its full range. Furthermore, plant equipment failures and associated malfunctions must be dealt with by taking into account prescribed safety and/or emergency operating procedures. Thus, plant automation to adapt to actual operations for normal as well as under unanticipated conditions is desirable. To continually monitor the system performance, the concept of learning automata [1,2] can be applied. The individual learning modules could be parts of the integrated control and decision-making system which dynamically responds to changes in the plant conditions. The learning agent reconfigures the system by switching to the controller that is most likely to achieve the desired performance. The strategy of reconfigurable control is time-dependent in the sense that an action is selected from a bank of pre-designed controllers at each sampling instant [3,4]. Failure to activate the appropriate control action would degrade the plant performance and safety. This situation may arise due to circumstances such as wrong identification of the plant operating condition due to noise, imprecise knowledge of the plant, and inadequacy of the controller itself. Therefore, the reconfigurable control system should also possess the capability to deal with uncertainties and function in a stochastic setting.

A learning automaton interacts with its environment and enables the control system to dynamically update actions based on environmental changes. Specifically, the automaton first chooses a particular action from the finite set of actions offered by the environment; the automaton is then penalized or rewarded by the environment which influences the choice of future action. In the present context, a specific action corresponds to one of the several controllers, and the automaton learns which is the most appropriate controller for a given plant condition. The fundamental principles of learning automata are explained in detail by Narendra and Thatachar [1,2].

2. SYSTEM DESCRIPTION

A deaerating feedwater heater, equipped with a water level controller and a pressure controller, has been chosen to investigate the feasibility of a reconfigurable control system based on learning automata to deal with power plant operations. Besides removing entrained air from the feedwater supply system, a deaerating heater provides an inventory of water for the main feedwater pump(s). A power plant deaerator is elevated relative to the feedwater pump inlet to provide a net positive suction head (NPSH). Due to this physical separation, the effects of changes in pressure and temperature in the deaerator water do not appear at the pump immediately but are separated by a transport delay. Specifically, pressure waves travel at the speed of sound through water while changes in water temperature are transported at a speed proportional to the feedwater flow rate. The interconnecting pipe is short enough to neglect pressure delays but long enough for the temperature delays to be significant for plant design and operation. These differences in transmission of events may diminish NPSH during transients. A severe loss of NPSH could ruin the feedwater pump due to cavitation possibly within a minute.

To avoid any such potential damage of the feedwater pump, both deaerator pressure and its decay rate must be controlled. The deaerator pressure is normally maintained by the flow of high quality steam bled from the main turbine into the deaerator while the water level is regulated by adjusting the flow of condensate water from the low pressure feedwater train. If the steam inlet flow is abruptly reduced, the deaerator pressure would rapidly decay which may cause cavitation at the feedwater pump.

A rapid pressure decay can be arrested by reducing the flow of the relatively cool condensate into the deaerator. At the same time, the water level in the deaerator must not drop

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below a minimum limit to ensure that the feedwater pump does not run dry. *During malfunctions* the reconfigurable control system must decide which action should be taken to manipulate the condensate water valve, i.e., whether to adjust the condensate flow to maintain the water level in the deaerator tank or to prevent the pressure decay as much as possible.

The low pressure feedwater heating system of the Experimental Breeder Reactor (EBR-II) at the Argonne National Laboratory site in Idaho has been chosen to demonstrate (via simulation experiments) the efficacy of reconfigurable control based on learning automata. Figure 1 shows the components of the simulated plant including: (i) the condensate pump which receives low pressure water from the condenser, (ii) an indirect-contact heater; (iii) the deaerator, the steam inlet valve, and the control valve to adjust condensate flow into the deaerator, and (iv) the deaerator level and pressure controllers that individually manipulate the condensate flow control valve. As indicated in Figure 1, the controller #1 manipulates the condensate flow control valve to maintain the deaerator water level, L(t). As an alternative to the controller #1, the controller #2 was made available for the learning system to maintain pressure, P(t), also by manipulating the condensate flow control valve. (The two controllers are not allowed to act *simultaneously* on the condensate flow valve.) Both controllers are designed using the single-input single-output proportional-integral algorithm. The proportional gain and reset time of the controllers #1 and #2 were determined on the basis of a simplified model of the deaerator. Although more advanced algorithms are likely to improve the system dynamic performance, these simple controllers facilitate a clear understanding of the operations of the learning mechanism.

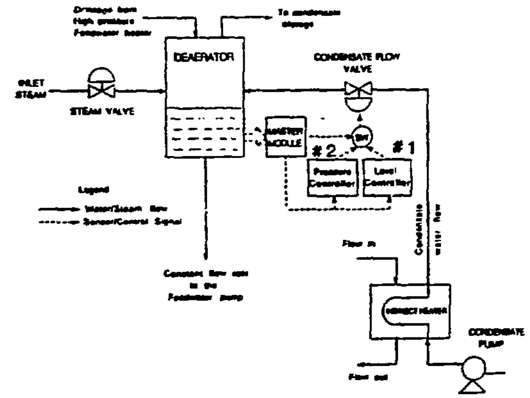


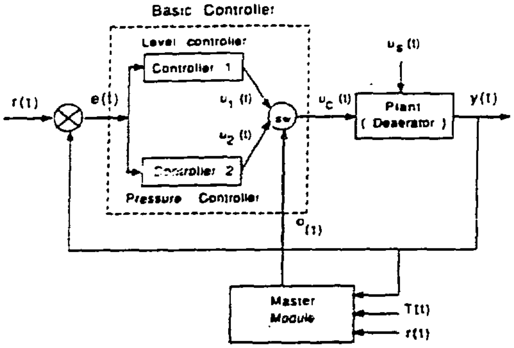
Figure 1. Schematic Diagram of the Simulated Deaerator System

3. RECONFIGURABLE CONTROL SCHEME

The concept of a reconfigurable control scheme that is capable of adjusting itself to changes in plant operating conditions has been introduced in [6]. Its application is illustrated on the deaerator system in Figure 1 by switching from one controller to the other. The operation of the reconfigurable control system can be divided in the following four steps: (1) identification of the plant operating condition, (2) evaluation of the current control performance, (3) updating of the individual controllers' performance based on current and previous plant *responses*, and (4) selection of a specific control law from the set of available ones. To integrate these tasks, a certain degree of *intelligence* is required. To this effect, learning behavior is incorporated in the reconfiguration scheme, and stochastic automata are specifically chosen because the plant is likely to undergo unstructured disturbances.

3.1. Structure of the Reconfigurable Controller

The simulated system consists of the *plant*, e.g., the deaerator as shown in Figure 1, and the *reconfigurable controller* which, in turn, is composed of two main components: the *basic controller module* and the *master module* as shown in Figure 2. Each of these modules are divided into submodules which are interconnected to satisfy both control and learning guidelines.



P(T) = Pressure in the Deaerator
L(T) = Level in the Deaerator
$T_{con}(t)$ = Condensate Water Temperature
$T_{fw}(t)$ = Feedwater temperature
$r_i(t)$ = Controller i's setpoint (i = 1,2)
$e_i(t)$ = Controller i's error (i = 1,2)
$u_i(t)$ = Output from controller i (i = 1,2)
$u_c(t)$ = Aperture of the condensate flow control valve
$u_s(t)$ = Aperture of the steam flow control valve

$r(t) = [r_1(t)\ r_2(t)]$
$e(t) = [e_1(t)\ e_2(t)]$
$y(t) = [L(t)\ P(t)]$
$T(t) = [T_{con}(t)\ T_{fw}(t)]$

Figure 2. Schematic Diagram of the Reconfigurable Control System

3.1.1. Basic Controller Module

In Figure 2, $u_c(t)$ corresponds to the action (of one and only one of the two controllers) that manipulates the condensate flow control valve. The control switching is based on the action selection signal $\alpha(k)\in\{1,\cdots,r\}$ where r is the number of available actions. (Note: r=2 in this example.) Thus, α(k) unequivocally selects a single controller at the k^{th} sampling instant (i.e., $u_c(t)=u_i(k)$, i=1 or 2) to act on the condensate valve. Upon selecting a $u_i(k)$, α(k) places the remaining controller(s) in tracking mode to accomodate bumpless tranfer.

3.1.2 Master Module

Based on predefined response criteria, the master module generates the action selection signal α(k) that will select the controller expected to perform better than the other controllers for the given plant conditions. The master module incorporates learning mechanisms to gain sufficient knowledge for identification of the correct controller. In this design, the master module is composed of the three submodules: (i) Performance evaluator (PE), (ii) Learning agent (LA), and (iii) Control action generator (CAG), as shown in Figure 3. Depending on the current plant operating mode, the master module updates the set point of the selected controller and feeds this information to the basic controller module.

3.1.2.1. Performance Evaluator

On the basis of the measured plant response, the performance evaluator (PE) interprets the current

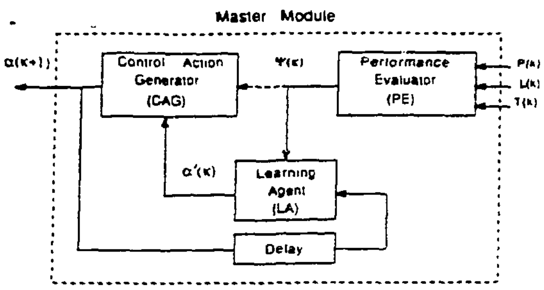
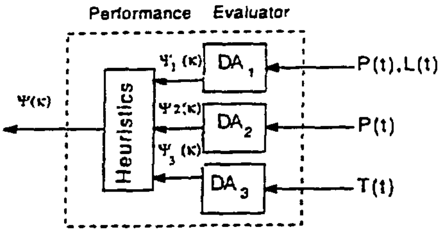


Figure 3. Schematic Diagram of the Master Module

performance of the selected controller as $\psi(k)\in\{-1,0,1\}$. If the performance criterion is satisfied, a reward condition is indicated by setting $\psi(k)=0$; otherwise, a penalty condition $\psi(k)=1$ is imposed. An inaction condition $\psi(k)=-1$ is asserted if the PE cannot arrive at a conclusion about the controller's performance. Three different decision logic are used for generating $\psi(k)$ where the resulting performance indices are denoted by $\psi_i\in\{-1,0,1\}$, i=1,2,3 as shown in Figure 4. The measurement history (including the current values) of pressure P and level L is used for computing ψ_1, the pressure decay rate for ψ_2, and temperatures of both the condensate and the feedwater flows for ψ_3. A brief description of each of these ψ_i's follows.



DA_i = Decision Algorithm i, i=1,2,3.

Figure 4. Schematic Diagram of the Performance Evaluator

Index ψ_1 bases its control preformance evaluation by identifying the plant operational zone of at each sampling instant. Specifically, the entire deaerator operating regime is partitioned into mutually exclusive but exhaustive zones such that the plant occupies exactly one of these zones at any instant of time. This performance decision is also made dependent on the history of the level and the pressure measurements. The idea is to evaluate the performances of both controllers on the basis of the current operating condition and predicted plant dynamics. Thus, if a process variable (e.g., level or pressure) experiences recovery while the other one is degrading, there is a potential of switching of controllers. ∎

Index ψ_2 is intended to reduce the pressure decay rate so that the potential problem of cavitation at the feedwater pump can be avoided. To this effect, a weighted average, $\delta P(k)$, of the pressure decay rate is obtained as follows

$$\delta P(k) = -\Big[\sum_{j=0}^{n(T)-1} \nabla P(k-j)\; w(j)\Big]/T$$

where the difference operator ∇ is defined as $\nabla f(k) := f(k)-f(k-1)$, the weight $w(j)$ is appropriately chosen (a possible choice is $w(j)=(j+1)^{-1}$), and the number n of past values of pressure readings over which the weighted average is taken is inversely related to the sampling interval T. Then, $\delta P(k)$ is compared with an *a priori* specified maximum pressure decay rate, δP_{max}, which is a function of the feedwater flow. If $\delta P(k)>\delta P_{max}$, the pressure controller is the recommended action.

Index ψ_3 bases the controller performance evaluation on the condensate and feedwater flow temperatures, T_{con} and T_{fw} respectively. Since $T_{con}<T_{fw}$ under normal circumstances, a reduction of the condensate flow into the deaerator would be appropriate for mitigating the pressure loss, even though it may be contrary to maintaining the water level. However, whenever $T_{con}>T_{fw}$, the pressure controller may not be the correct choice. The rationale is that level control, under these circumstances, would increase both level and pressure by augmenting the condensate flow. This temperature-dependent criterion is implemented by setting ψ_3 to 1 if the pressure controller is active and $T_{con}>T_{fw}$; otherwise, ψ_3 is set to 0. ∎

At each sampling instant k, the signal ψ is heuristically generated as a combination of ψ_1, ψ_2 and ψ_3 as follows.

$$\psi = \begin{cases} \psi_3 & \text{if } \psi_3=1 \text{ and any values of } \psi_1 \text{ and } \psi_2; \\ \psi_2 & \text{if } \psi_3\neq1,\ \psi_2\neq-1, \text{ and any value of } \psi_1; \\ \psi_1 & \text{if } \psi_3\neq1, \text{ and } \psi_2=-1. \end{cases}$$

The signal $\psi(k)$ is an input to both the learning agent and the control action generator. If the performance evaluator cannot make a decision on the current controller's performance during a given sampling period k (i.e., $\psi(k)=-1$), the learning mechanism is "frozen"; that is, the automaton states are held constant, and any switching from one controller to another is inhibited. On the other hand, if the performance evaluator does make a decision (i.e., $\psi(k)=0$ or 1), then not only the learning automaton states are updated but also $\psi(k)$ serves as the forcing function in the automaton difference equations.

3.1.2.2. Learning Agent

The learning agent (LA) is essentially implemented using the concept of stochastic automata. The LA, at the sampling instant k, proposes a specific controller for the (k+1)st sampling period. The inputs to the LA are the decisive response of the PE, i.e., $\psi(k)$ being 0 or 1, and $\alpha(k)$ from the control action generator serves as the identity of the current controller. The output $\alpha'(k+1)$ of the LA is only a proposed choice for controller selection because the final decision, $\alpha(k+1)$, is made by the control action generator.

3.1.2.3. Control Action Generator

The control action generator (CAG) shown in Figure 5 decides which one of the available controllers should act upon the plant. The CAG governs switchings from one controller to another based on the plant response. Any switching is performed in a bumpless manner. When PE fails to arrive at a decision, i.e. $\psi(k)=-1$, such switching is inhibited during the k^{th} sampling period. To reduce erratic control transitions, the CAG uses a procedure based on sequential testing to suppress the spurious fluctuations in the action $\alpha'(k)$. These fluctuations may occur due to measurement noise, plant disturbances, and modeling uncertainties of the reinforcement scheme.

The CAG also contrains the control selection process of the master module. The decision $\alpha'(k)$, proposed by the LA, may violate plant specifications because the LA is completely unaware of the plant operational constraints. Whenever any such constraint is violated, the proposed action α' is overridden by the CAG according to certain rules, and the

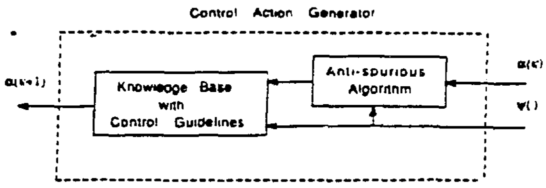


Figure 5. Schematic Diagram of the Control Action Generator

next "best" choice is accepted as the action α for controller selection.

4. SIMULATION EXPERIMENTS AND RESULTS

The performance of the reconfigurable control scheme, described above, has been evaluated via interactive simulation using the Modular Modeling System (MMS) [7] and the Advanced Continuous Simulation Language (ACSL) [8]. The Discrete Linear Reward Penalty scheme (DL_{RP}) [9] was chosen as the reinforcement scheme in the learning agent with the number of steps being equal to 6.

Figure 6 shows the architecture of this microprocessor based control for simulation experiments. The Network 90 distributed process control system [5] was used to implement the reconfigurable scheme. The simulated plant (running on the VAX mainframe) calculates the feedwater flow based on the inlet steam flow, condensate flow, deaerator level, pressure, and condensate and feedwater temperatures. Using these values, a program which emulates the master module (running also on the VAX) evaluates the performance of the currently active controller and then decides which controller should be selected at the sample. Both the current plant conditions and the decision (i.e., the action signal $\alpha(k)$ and set points of the two controllers) of the master module are communicated to the multifunction controller of the Bailey system through a RS-232C serial line. The multifunction controller then takes the simulated plant condition and the Master Module's commands to implement the control functions. The actuator command (i.e., position of the condensate valve) is then calculated and transmitted to the VAX so that the new plant conditions can be simulated.

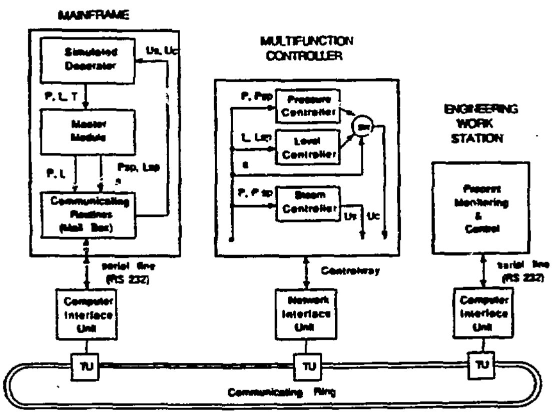


Figure 6. Simulation of the Distributed Control System

One of the various scenarios that were simulated to test the reconfigurable controller, is abrupt changes in the steam inlet flow into the deaerator as shown in Table I.

Table I. Disturbances in Inlet Steam Flow

Time Range in # of samples	Steam Flow in percent
0 — 10	80
11 — 100	30
111 — 160	50
161 — 310	75
311 — 450	85
451 — 500	100

The responses of the pressure $P(t)$ and level $L(t)$ are presented in Figures 7 and 8, respectively, for comparison of the original (i.e., without learning) and the reconfigurable schemes.

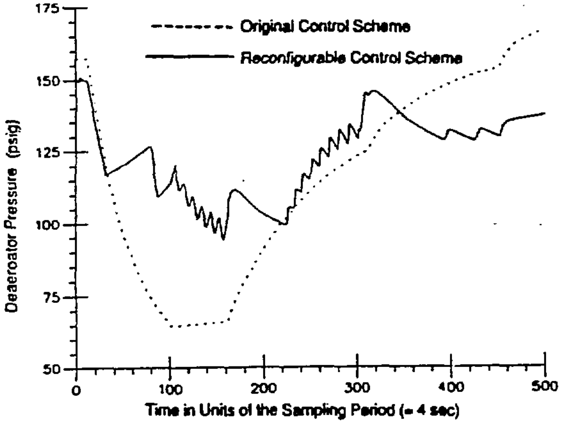


Figure 7. Deaerator Pressure Transients

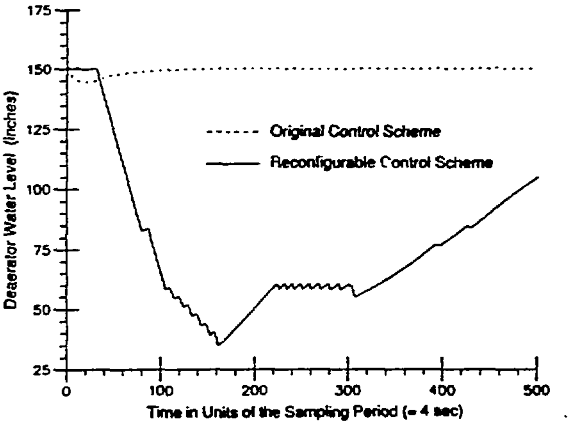


Figure 8. Deaerator Level Transients

As mentioned earlier, the response of the deaerator during a loss of steam flow is expected to be a reduction in pressure to the point that the plant must be shutdown to prevent damage to the feedwater pumps due to lack of available suction head. With the normal level controller still in operation, the flow of relatively cool condensate is increased to makeup for the loss in mass flow from the steam. However, this control action to maintain level at the set point aggravates the pressure decay as seen at the beginning of transients in Figure 7. Under these circumstances, switching to the alternate pressure controller would reduce the flow of cool condensate so that the deaerator pressure can be maintained while allowing the level to drop as seen in Figure 8. The learning system, instead of having a preplanned schedule, decides the appropriate control action by monitoring of the process variables.

It is seen in Figures 7 and 8 that switching to the pressure controller from the level controller arrests the pressure decay at the expense of letting the level drop. Under the level controller in the original scheme, the pressure continues to fall. The reconfigurable scheme arrests the pressure decay within ≈ 30 samples and does not allow $P(t)$ to drop below 90 psig whereas, in the original scheme, the pressure continues to decay until the steam flow is partially restored at at 110th sample when $P(t)$ has dropped to ≈ 65 psig.

The reconfigurable scheme causes switching between the two controllers. Although the controllers are appropriately interlinked to ensure these switchings to be *bumpless*, this phenomenon is a source of potential instability in the actual plant which is prone to noise and disturbances. Whenever a switching from the pressure controller to the level controller takes place, the condensate flow is increased from a small to an almost maximum to quickly restore the level. These variations in operating conditions occur due to the reverse effects that the two controllers exert over the plant. More sophisticated algorithms and a larger number of alternative control actions would potentially reduce the frequency of switchings and thereby improve the performance of the reconfigurable scheme. For example, an advanced multivariable control law such as LQG [10,11] or one using the fuzzy logic [12] would simultaneously minimize errors in the critical process variables so that the level is more effectively recuperated while maintaining the pressure within the safety ranges.

5. SUMMARY AND CONCLUSIONS

A reconfigurable control scheme is proposed which, unlike a preprogrammed one, uses stochastic automata to learn the current operating status of the plant by dynamically monitoring the system performance and then switching to the appropriate controller on the basis of the observed performance. The potential applicability of this reconfigurable control scheme to electric power plants has been investigated. A deaerating feedwater heater, equipped with a water level controller and a pressure controller, has been chosen to study the feasibility of reconfigurable control in power plant operations. Simulation experiments have been conducted on the basis of a model of the Experimental Breeder Reactor (EBR-II) at the Argonne National Laboratory site in Idaho. The results show that the reconfigurable control scheme is capable of providing a sufficient margin for the net positive suction head at the feedwater pumps under loss of steam flow into the deaerator. Under similar circumstances, the existing controller in the deaerator would be incapable of maintaining the pressure and its decay rate within the safe margins, and thereby force the plant operator to take additional measures to protect the feedwater pumps. The learning agent in the reconfigurable controller of the deaerator is capable of taking a correct action in the (unusual) event of the condensate water being warmer than the feed water. This example shows how the control system can learn to react to unanticipated circumstamces which could be difficult for human operators to handle within time constraints.

Incorporation of learning capabilities within the reconfigurable control scheme is promising for unanticipated and uncertain plant conditions for which preprogrammed control algorithms are apparently difficult to formulate. Both the performance evaluator and the set of alternative controllers are critical for the reconfigurable control scheme, and may rely on a combination of analytical and heuristic techniques. While the general structure of the performance evaluator is specifically dependent on the given application, the individual control algorithms are more likely to be formulated by taking advantage of the existing model-based and rule-based design methodologies.

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