Accommodating Power Plant Anomalies via an Artificial Neural Network-Based Reconfigurable Control

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ABSTRACT

A reconfigurable control strategy has been developed using a feed-forward Artificial Neural Network (ANN) implemented on a Bailey Network 90 digital control system requiring relatively minor modifications to the plant controller. An experimentally verified simulation of a secondary system's deaerating feedwater heater of a nuclear power plant was used to demonstrate the feasibility of the concept. The controller uses the ANN to decide when to switch from normal level control to alternate pressure control (via the level control valves) in the event of a rapid pressure decrease, possibly due to loss of feedwater heating, i.e., a phenomenon known as deaerator quenching. A prolonged rapid pressure decrease would result in feedpump cavitation (i.e., Net Positive Suction Head less than zero) due to the change in pressure reaching the pump suction before the corresponding change in saturation temperature. The ANN uses the deaerator level, pressure, and rate of change of pressure to develop a system status signal (i.e., reconfiguration switch signal) between 0.0 and 1.0. The existing level controller, with some minor modifications, is reconfigured to a pressure controller upon receiving a switch signal of 0.485. When tested with a simulated pressure regulator malfunction the reconfigurable control scheme displayed superior performance (compared with the original system) by arresting the pressure decrease and maintaining NPSH above zero for a prolonged period of time.

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KEYWORDS

artificial neural network, reconfigurable control, power plant dynamics, power plant anomalies, power plant control.

1. INTRODUCTION

The Experimental Breeder Reactor II was operated by Argonne National Laboratory at the Idaho National Engineering Laboratory. The reactor was decommissioned in the late 1990s and at the time was the only operating experimental power reactor in the United States of America. The EBR-II power plant had as its primary system a sodium-cooled pool-type fast reactor rated at 62.5 MW thermal. An intermediate sodium loop removes heat from the primary system sodium and transfers the energy to a conventional steam electric-power-producing cycle that generates 20 MWe. The major sequence of components in the steam plant (Turso, 1993) (which are found in fossil-fueled power plants as well) consists of a condensate pump, closed feedwater heater, deaerating heater, feedwater pump, two high-pressure closed feedwater heaters, steam drum, evaporators, superheaters, and turbine-generator system. Of the feed system heaters, the deaerator is unique in that it is of the direct contact type i.e., the condensate to be heated and the steam doing the heating are in direct contact. This configuration results in the deaerator pressure being tightly coupled to the incoming condensate mass flow and temperature. Figure 1 shows a schematic of the portion of the steam plant where the deaerator is located.

For proper operation during steady state or transient conditions, a minimum feedwater-pump suction pressure or Net Positive Suction Head Required (NPSHR) must be maintained. If pump inlet conditions result in a Net Positive Suction Head (NPSH) below the value specified by the manufacturer, then vapor is formed at the pump suction (i.e. cavitation) possibly damaging the feedpump internals and halting the flow of feedwater to the steam generators.

To address this scenario, an ANN is used to reconfigure the deaerator level controller to control pressure upon a rapid loss of steam flow into the deaerator, maintaining feedpump NPSH above zero for as long as possible

Fig. 1: Portion of the steam plant including the deaerating feedwater heater (deaerator)

and providing plant operator extra, precious time to fully assess the situation and provide corrective actions. Upon reconfiguration, the flow of relatively cool condensate into the heater is throttled (which sacrifices heater level for the period of reconfiguration), allowing for the pressure to be maintained.

A nonlinear simulation is used to demonstrate the feasibility of the ANN-based reconfigurable controller via hardware-in-the-loop simulation testing. The effect necessary for the reconfigurable control of the deaerator, an increase in pressure due to a reduction in condensate flow, was experimentally verified (Turso, 1993). The same simulation was used to validate a Discrete Event System (DES)-based Controller (Garcia et al. 1991), designed to provide a similar function as the ANN on the same process, before demonstrating it on the actual plant. The DES had been tested on the plant (Garcia et al., 1995; Edwards et al., 1993), but the plant was decommissioned shortly after testing. Thus, the experimentally verified simulation is considered adequate for the purposes of demonstrating the effectiveness of the ANN-based reconfigurable controller and comparing its performance to that of the DES-based system.

2. PROCESS CHARACTERISTICS AND EXISTING CONTROL

Figure 2 indicates that the EBR-II deaerator is vertically oriented. Normal liquid level of near 170 inches represents an approximate six-minute supply of feedwater at full-power conditions and is regulated by manipulating the condensate flow control valves. As shown in Fig. 2, there are actually two parallel flow paths, with associated flow control valves (P5-VC-619 and P5-VC-619A), for regulating condensate flow at EBR-II. Steam header pressure, which supplies the deaerating steam, is regulated to 150 psig by manipulating a valve in a steam extraction line (P5-VC-510) taken from the main steam header or from the plant auxiliary steam supply system.

Control of these process variables (pressure and level) is performed by single loop PI control algorithms⁵ implemented using standard control block programming in Bailey NETWORK 90 microprocessor-based controllers (Bailey, 1990a, 1990b). There are two feedwater pumps, only one of which is used in normal operation. At full power conditions, it takes approximately 12 seconds for water leaving the deaerator to arrive at the inlet to feedwater pump 1 and approximately 24 seconds for water to arrive at the inlet to feedwater pump 2. The deaerator is elevated approximately 25 feet above the feedwater pump suction to provide required net positive suction head (NPSH) to the feedwater pumps. Due to the transport delay from the deaerator to the feedwater pumps, however, there can be a significant reduction in NPSH if there is a rapid reduction in deaerator pressure. Pressure effects in a deaerator are almost immediately propagated to the feedwater pump inlet, whereas change of internal energy at the pump inlet is delayed by the transport time. This potential reduction in NPSH during transients motivated the design of the neural network based fault-accommodating reconfigurable controller.

For proper operation during steady state or transient conditions, a minimum feedpump suction pressure or Net Positive Suction Head Required (NPSHR) must be maintained. This value is specified by the manufacturer and is constant for all operating conditions. If pump inlet conditions result in a Net Positive Suction Head (NPSH) below this value, vapor is formed at the pump suction (i.e. cavitation) possibly damaging the feedpump internals and halting the flow of feedwater to the steam generators. This effect is described quantitatively via Net Positive Suction Head Available (NPSHA).

Fig. 2: Deaerator, supporting hydraulic network, and control system.

The value of the NPSHA is a function of the total height of the column of water above the pump suction (H_{st}), suction line losses (H_{loss}), vapor pressure of the water at the pump inlet temperature (H_{vap}) and the absolute deaerator pressure in feet (H_{dea}). In equation form,

$$NPSH = H_{dea} + H_{st} - (H_{vap} + H_{loss} + NPSHR) . \quad (1)$$

Due to the term H_{vap} in Eq. (1) the value of the feedpump NPSH is not only a function of the deaerator level and pressure but of the rate of change of pressure decent as well. For reconfigurable control to be effective, a significant amount of coupling must exist between the controlled variables. In the case of the deaerator, where the pressure is affected by the mass flow and temperature of the condensate into the deaerator, pressure can be manipulated via condensate flow. During normal operation, condensate flow is altered to provide the deaerator level necessary to maintain the NPSHR and to prevent feedwater pump cavitation. During steady state operation, the actual feed pump suction head is not only a function of level but of deaerator pressure as well. A relatively small drop in level has little impact on NPSH. A comparatively small decrease in pressure could decrease the NPSH enough to result in pump cavitation. During transient operation, where the rate of change of pressure decrease may be relatively large, the change in pressure may actually reach the pump suction before the corresponding decrease in saturation temperature, which progresses at a speed comparable to the mass flow rate out of the deaerator. If this results in a situation in which the temperature at the pump suction is actually higher than the corresponding saturation temperature, then 'flashing' at the eye of the pump (cavitation) results with a corresponding loss of feedwater flow to the steam generators. Major damage to the feedpump would result as well.

During normal operation of deaerator, the level PI controller is 'ignorant' of the deaerator pressure. Figure 3 shows the response of the system to a simulated pressure regulator malfunction, resulting in a steam valve closure of 20%, at 40 and 62MW (full power). For both power levels, the deaerator level remains at approximately the steady state value. The deaerator pressure displays a continued decrease in part due to the inhibited flow of steam into the system. Maintaining the prescribed level aggravates the pressure decrease by allowing in a constant amount of relatively cool condensate into the deaerator. Feed pump cavitation (i.e. $NPSH < 0$, the horizontal lines in Fig. 3) occurs approximately 16 seconds into the transient for both power levels. To curtail this effect, the condensate flow must be manipulated in such a way as to arrest the pressure decrease for as long as possible, allowing the decrease in saturation temperature to "catch up" to the corresponding decrease in pressure at the pump suction. A learning automata based reconfigurable controller, which manipulates condensate flow to control pressure during a

Fig. 3: System response to pressure regulator malfunction (no reconfiguration). Uppera; response at 40 MW
poer level; lower: response at 62 MW power

rapid pressure decrease, has been successful in maintaining feedpump NPSH (Garcia et al., 1995; Edwards et al., 1993; Franklin et al., 1994) for this scenario.

3. ANN-BASED RECONFIGURABLE CONTROL

The three measurable variables necessary for an adequate assessment of the status of the deaerator system (for diagnosing an impending feedpump failure) are level, pressure, and rate of change of pressure. A “supervisor” is required to determine the status of the plant, decide which control mode (pressure or level) is the most appropriate for the present plant conditions, and provide a stable switch signal for reconfiguration. In other words, a mechanism that maps the three plant parameters, level, pressure and rate of change of pressure into a reconfiguration switch signal is required.

A feedforward neural network (Wasserman, 1989) was chosen to perform the task of mapping the deaerator level, pressure, and rate of change of pressure into a switch signal that is used to reconfigure between the normal Level controller and pressure control. Feedforward ANN are unconditionally stable, i.e. the absence of output feedback ensures stability given a bounded input. Thus, unconditional stability of the switch signal was a prime motivation for choosing this type of ANN. The mapping provided by this type of network is static, in other words, the network output remains unchanged unless an input signal (or signals) is changed. An additional feature of neural networks, the ability to generalize for unanticipated plant conditions and still provide a reasonable value for the switch signal, was essential to keep the amount of expert knowledge required (i.e. number of training pairs) to a minimum. The network (Fig. 4) consists of three input “pseudo” neurons, three hidden layer neurons and one output neuron providing the switch signal for reconfiguration. The simplicity of this configuration led to easy implementation on the actual digital control system (DCS) hardware. The synaptic weights were determined via the MATLAB Neural Network Toolbox software package (Demuth & Beale, 1998). Training of a feed-forward ANN is best performed using input and output pairs that are scaled between 0 and 1.0. Thus, the level and pressure inputs to the network had to be divided by 100. It was not to scale the rate of change of pressure. The reconfiguration switch signal (i.e. network

output) was designated to be between 0 and 1.0. As shown in Table 1, a switch signal of 0.5 was designated for normal operating conditions.

Fig. 4: Feedforward ANN used to determine reconfiguration switch signal.

TABLE 1

Example Reconfigurable Control ANN Training Pairs

dP/dt	Level / 100	Pressure /100	Desired Network Output
-0.55	0.168	0.140	0.45
0.25	0.145	0.135	0.55
0.0	0.168	0.152	0.5
-0.55	0.168	0.110	0.35
-0.25	0.168	0.142	0.475
-0.1	0.168	0.145	0.485
0.1	0.15	0.14	0.525
0.25	0.145	0.135	0.535
0.25	0.120	0.125	0.6

The corresponding process variables are scaled and required as inputs. A value of 0.6 is designated as the network output corresponding to a switch back to level control (level fairly low and pressure increasing). An output of 0.45 corresponds to a worst case scenario (pressure low and decreasing at the maximum possible rate). The values for the remaining training sets were chosen to provide a uniform distribution of possible scenarios between these two sets of operating conditions.

Figure 5 shows the integration of the neural network “supervisor” into the existing deaerator control system. The supervisor monitors the deaerator level, pressure, and rate of change of pressure. After processing these variables, a suitable switch signal is determined corresponding to the state of the process. The signal is fed to a switch within the level controller. The level controller utilizes two Proportional Integral Derivative (PID) controller algorithms, one for valve 619 and the other for valve 619A, with only the proportional and integral control actions used. The PI algorithm (Franklin et al., 1994) takes the error between the actual deaerator level and the preset desired level (“setpoint”), multiplies the error by a gain factor, and adds this to the integral of the error (to minimize process variable offset with respect to the setpoint). During normal operations, each uses the current deaerator level to determine a suitable valve position. Upon receiving an appropriate switch signal from the supervisor, control of the valves 619 and 619A is transferred from the level control PI controllers to the alternate pressure control PI controllers. The alternate PI controllers use the deaerator pressure to determine a suitable position of the condensate-flow control valves. The action of the alternate pressure controller is opposite of that used for level control, i.e., to increase level, valves 619 and 619A must be opened, to increase pressure these valves must be closed. Upon reconfiguration, the level controller setpoint “tracks” the current deaerator level for a “bumpless” transfer from alternate pressure control back to normal level control.

4. CONTROLLER IMPLEMENTATION AND TESTING

Testing of the ANN based reconfigurable control strategy was performed with a “noisy” version of the EBR-II condensate/deaerator system simulation (Turso, 1993). Process and/or sensor noise was added to the deaerator level

Fig. 5: Integration of the Neural Network Supervisor into the existing deaerator control system.

(standard deviation of 0.2") and pressure (standard deviation of 0.2 psi) process variables to provide a more realistic environment for testing. Controller testing performed for two cases—i.e., two sets of initial conditions corresponding to 40 and 62 MW power levels. In both cases, the pressure regulator was placed into the manual mode of operation, and the steam valve position demand signal decreased by approximately 20%. This event could represent a failure of the pressure regulator, malfunction of the steam valve or a rupture in the steam line to the deaerator.

Before use on the actual plant, the controller should be tested in a “pseudo” real world environment. The Bailey system represents the actual control hardware found at EBR-II. This system is typical of the digital control systems found at other plants in the power and process industries. A controller implemented and successfully tested in this type of environment could easily be adapted for use on the actual system—thus, the rationale behind the “hardware-in-the-loop” method of controller testing. The “hardware” in this case being the Bailey Network 90 DCS.

The Bailey Network 90 micro-processor based control system has a reprogrammable capability that is essential for advanced controller development. The system is modular in construction, i.e. each controller module, Computer Interface Unit (CU), Loop Interface Unit etc. can be slid into and out of a module mounting unit. The individual modules communicate through a module bus (data highway), and the entire system can exchange data with a personal computer (or work station) through a Computer Interface Unit or serial port module (Bailey, 1990a, 1990b).

Controller algorithms are programmed via a Bailey Control Co. supplied computer aided design (CAD) program. The engineer has a choice of over one hundred control or control related function blocks from which to choose. A controller program is developed by “calling up” the necessary blocks to perform the desired control function. Once properly arranged, the blocks are connected via solid or dashed lines. The completed program is compiled and downloaded into the designated controller module for execution. For the reconfigurable control strategy, a Multifunction Controller and a Basic Controller module (with similar programming as found in the actual plant) were used.

5. RESULTS AND DISCUSSION

Figure 6 presents the 40 MW system response to a hypothesized failure scenario i.e., a steam valve malfunction, resulting in a valve closure of 20%. The level controller initially aggravates the pressure decrease by continuing the flow of relatively cool condensate into the deaerator. This flow also immediately halted. A point is reached where the system status improves to an acceptable value (switch signal equal to 0.495) with a corresponding change

Fig. 6: System response to a 20% decrease in steam valve position, 40 MW power level. (upper) Process variables, (lower) NPSH

back to level control. Thus, with the pressure decrease halted at the appropriate point, the decrease in saturation temperature of the system is given time to “catch-up” to the pressure at the feedpump suction, eliminating the possibility of pump cavitation due to the “flashing” at the eye of the pump results in a rapid decrease in NPSH. As the anomaly progresses, the output of the ANN decreases until the status of the system has degraded to the point where a reconfiguration from level to pressure control is enforced.

Immediately after switching, the controller sacrifices level by decreasing the flow of condensate into the deaerator. The pressure (and NPSH) decrease is immediately halted. A point is reached where the system status improves to an acceptable value (switch signal equal to 0.495) with a corresponding change back to level control. Thus, with the pressure decrease halted at the appropriate point, the decrease in saturation temperature of the system is given time to “catch-up” to the pressure at the feedpump suction, eliminating the possibility of pump cavitation due to the “flashing” at the eye of the pump (i.e. $\text{NPSH} < 0$). For the duration of the malfunction, 600 seconds, NPSH was kept greater than zero. This is a significant improvement over the system response without reconfiguration (Fig. 3).

Figure 7 presents the 62 MW system response to a prolonged steam line malfunction, again represented by a steam valve closure of 20%. The condition was maintained for approximately 500 seconds. The controller maintains a positive NPSH for approximately 300 seconds. For the majority of the remaining 200 seconds, the feedpump NPSH remains greater than zero, only occasionally dropping below 0 with a minimum NPSH of -0.86. For centrifugal pumps handling hydrocarbons and “hot” water (i.e. the EBR-II feed pump) operation with NPSH less than zero may be permitted for brief periods of time (Westaway & Loomis, 1979). Thus, in all likelihood the feedpump would not fail and remain in operation, again a marked improvement over the system performance without reconfiguration.

The system dynamics are more rapid at 62 MW (full power) compared to lower power operating conditions. Thus, malfunctions occurring at this power level represent worst-case scenarios for this plant. With a higher flow rate out of the feedpump, the deaerator level would decrease faster upon reconfiguration. As mentioned previously the neural network supervisor is a static mapping. Thus, the dynamics of the neural network (i.e. the reconfiguration switch signal) depend on the rate at which the process variables change. As the rate of change of the process variables increase, so does the rate of change of the switch signal. As the state of the system deteriorates, resulting in a lower ANN output (i.e. deaerator level and pressure decreasing), the smaller maximum value of the switch signal approaches the upper dead band limit (.495), resulting in more rapid controller reconfiguration. The combination of the supervisor dynamics and the increased rate of system degradation (due to the plant dynamics at 62 MW) resulted in the behavior illustrated in Fig. 7.

Fig. 7: System response to a 20% decrease in steam valve position, 62 MW power level. (upper) Process variables, (lower) NPSH.

The ability of the ANN to accommodate changing plant dynamics due the nonlinear nature of the process being controlled, i.e., the 40 MW plant dynamics as well as the 62 MW plant dynamics, is also demonstrated.

6. CONCLUSION

A reconfigurable control strategy has been developed using a feedforward Artificial Neural Network (ANN) implemented on a industrial-

grade digital control system, the Bailey Network 90 DCS. A simulation of a subsystem of the Experimental Breeder Reactor II steam plant, the deaerating feedwater heater, was used to demonstrate the feasibility of the concept. The controller uses the ANN to decide when to switch from normal level control to alternate pressure control (via the level control valves) in the event of a rapid pressure decrease. A prolonged rapid pressure decrease would result in feedpump cavitation (i.e. Net Positive Suction Head < 0) due to the change in pressure reaching the pump suction before the corresponding change in saturation temperature. The ANN uses the deaerator level, pressure, and the rate of change of pressure to develop a system status signal (i.e. reconfiguration switch signal) between 0.0 and 1.0, with 0.5 representing normal operating conditions. The existing level controller, with some minor modifications, is reconfigured to a pressure controller upon receiving a switch signal less than 0.485. Return-to-level control is indicated when the switch signal recovers above 0.495.

When tested with a simulated pressure regulator malfunction, the reconfigurable control scheme displayed superior performance, compared with the original system, by arresting the pressure decrease and maintaining NPSH above zero for a prolonged period. The original system would have aggravated the situation by allowing a constant amount of relatively cool condensate into the deaerator in an attempt to maintain the prescribed level. The ANN-based and the DES-based reconfigurable controller (designed for and tested on the same system (Garcia et al., 1995; Edwards et al., 1993; Franklin et al., 1994) produce comparable results for similar anomalies (steam-valve malfunctions or steam-line ruptures). The DES-based controller is significantly more complicated requiring expert knowledge exceeding 170 rules and substantial amounts of C programming (hundreds of lines of code).

In contrast, the ANN based reconfigurable controller (a) required a training set consisting of 25 training pairs, (b) is relatively simple to program using standard controller functions and, (c) because of the simplicity of feedforward ANN, is relatively easy to understand. The ability of the ANN to accommodate changing, unanticipated plant dynamics due the nonlinear nature of the process being controlled, one of the major factors for use of the DES-based system, is also demonstrated.

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