Processor-in-the-Loop Simulation and Multivariable Control System Design for Pressurizer System in Nuclear Power Plants

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Date: 2025-02-17T00:00:00+00:00

Abstract

One of the famous and energy-efficient types of nuclear power plants is the pressurized water reactor (PWR). The pressuriser (PZR) system is essential for the safe functioning of a PWR as it regulates primary coolant pressure variations during normal operations and maintains pressure within designated boundaries. The PZR unit in the PWR is a Multi-Input Multi-Output (MIMO) and nonlinear dynamic system. Accordingly, the control strategies of the PZR system are too complex. The pressure and water level of PZR directly affect the performance operation of the PWR load power. Therefore, an adaptive PID-based fuzzy logic controller is proposed in this paper to control both the PZR pressure and water level with the derivation of their control signals. The PZR model with the proposed controllers is implemented using the MATLAB/Simulink environment. Also, this research aims to drop the proposed control systems in practice firmware and ensure low cost and less memory consumption of the processor. Therefore, the proposed controllers are validated by the processor in the loop (PIL) test using the STM32F407 discovery kit. The results of different PZR operation scenarios show the improvement of PZR water level performance and pressure using the proposed adaptive PID controllers, with a remarkable coincidence between their simulation and PIL implementation response.

Full Text

Preamble

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Abstract

The pressurized water reactor (PWR) represents one of the most prominent and energy-efficient nuclear power plant designs. The pressurizer (PZR) system is essential for safe PWR operation as it regulates primary coolant pressure variations during normal operations and maintains pressure within designated boundaries. The PZR unit in a PWR constitutes a Multi-Input Multi-Output (MIMO) nonlinear dynamic system, making its control strategies inherently complex. Since the pressure and water level of the PZR directly affect PWR load power performance, this paper proposes an adaptive PID-based fuzzy logic controller to regulate both PZR pressure and water level through derived control signals.

The PZR model with the proposed controllers is implemented in the MATLAB/Simulink environment. This research also aims to deploy the proposed control systems in practical firmware while ensuring low cost and minimal memory consumption. Therefore, the proposed controllers are validated through processor-in-the-loop (PIL) testing using the STM32F407 discovery kit. Results from various PZR operation scenarios demonstrate improved water level and pressure performance using the proposed adaptive PID controllers, with remarkable consistency between simulation and PIL implementation responses.

Keywords: Nuclear Power Plant, PZR System, Adaptive PID Control, Fuzzy Control, PIL

I. Introduction

In Pressurized Water Reactors (PWR), the pressurizer (PZR) is an essential component of the primary circuit (PC) that maintains reactor coolant system (RCS) pressure at predetermined setpoints during steady-state operation. During transient operations, it controls resultant pressure variations within allowable tolerances [1, 2]. The PZR compensates for positive and negative fluctuations arising from load power transients by maintaining water and steam saturation in balance to preserve PC pressure. During these rapid operational changes, the reactor continues operating without shutdown. The PZR also prevents primary loop overpressure during various reactor accidents while preserving system integrity, acting as a buffer container that absorbs rapid changes in primary loop water volume [3].

Consequently, PZR pressure and water level control are critical for safe PWR operation. Pressure control is achieved through electrical heaters and spray valves. The PZR comprises a spray system, electrical heater units, safety valves, and measuring devices. PC pressure decreases when the steam region is sprayed with low-temperature coolant flowing through spray valves, while the electrical heater unit increases PC pressure by heating the coolant. Accurate modeling of the PZR' s thermal-hydraulic behavior during transients is essential for achieving control objectives [4-6]. PZR behavior is exceedingly complex due to its nonlinear characteristics, significant inertia, time-varying parameters, and unpredictable open-loop dynamics [7].

Previous studies have employed alternative mathematical models with simplified assumptions for PZR thermal-hydraulic simulation. For instance, [8, 9] developed a non-equilibrium three-region model based on mass and energy conservation laws. Reference [10] demonstrated that PC variations influence two-region thermal-hydraulic models, while [11] presented a four-region model with fewer assumptions than other models. A non-equilibrium control-oriented model for PZR dynamic behavior was developed in [12], and multi-region models composed of three layers divided into multiple control volumes were introduced in [13].

Various specialized controllers have been applied to PZR system modeling to enhance pressure control efficiency during secure PWR operation. Researchers have employed linear, artificial intelligence-based, and nonlinear controllers. A fuzzy controller based on artificial neural networks (ANNs) was developed for PZR pressure control in [14], while [9] proposed a fuzzy-logic-based approach for evaluating constant pressure setpoint control schemes. Reference [15] presented a PZR pressure control method based on an adaptive prediction algorithm. In 2018, [4] applied Particle Swarm Optimization (PSO) to optimize PID controller gains for PWR power-level control. A fuzzy PID controller regulated the linearized PZR model water level in 2011 [6], and a single neural PID controller was proposed for PZR pressure control in 2013 [6]. The Fuzzy-PID controller was first applied to nuclear reactor power control systems in 2013, tuned using Genetic Algorithms (GA) [16]. Evolutionary algorithms investigated multi-objective optimization of PID parameters for PZR pressure and level control systems [17], and in 2019, a linearized non-equilibrium three-region PZR model was developed with PID controllers for pressure and water level regulation [8].

The nonlinearity and complexity of PZR mathematical models have led researchers to focus on linearized models or AI-based techniques for designing pressure and level control systems. However, these controllers may not accurately reflect real-world performance evaluation. Furthermore, most advanced intelligent controllers treat the pressure and level control mechanisms as independent Single-Input Single-Output (SISO) systems, despite their interdependence during shrink and swell phenomena in PZR operation.

Various control algorithms exist for PZR systems, but direct practical implementation is challenging. Building physical prototypes for testing and evaluation entails lengthy design processes, increasing costs and occasionally posing safety risks. Offline simulation platforms serve as widely used validation and verification tools for investigating system behavior. Between simulation and hardware implementation lie several development phases. Embedded software typically follows the V-cycle development approach [18, 19], while X-In-The-Loop represents a model-driven testing technique. These tests offer four configuration tiers: MIL (Model-In-The-Loop), SIL (Software-In-The-Loop), PIL (Processor-In-The-Loop), and HIL (Hardware-In-The-Loop) [20]. Each configuration contributes to development by bridging the gap between mathematical models and firmware executing on standalone microprocessor platforms.

MIL configuration serves as the starting point for model-driven system approaches, involving basic simulation to examine both controller and plant models. The primary objective is creating and validating test cases on a high-precision floating-point arithmetic platform to evaluate model behavior and performance. This stage produces reference output test results for subsequent phases and allows rapid identification and correction of mathematical controller model defects, occurring early in the development cycle.

In Software-In-The-Loop (SIL), executable code running in fixed-point arithmetic on the same computer platform replaces the MIL model. This stage helps developers quickly identify poor memory allocation decisions. These operations are typically performed on a single integrated PC platform. The SIL step can be bypassed if the controller system will run on hardware with a dedicated floating-point unit in its CPU data-path.

The PIL (Processor-In-The-Loop) test extends beyond the PC platform [21, 22], incorporating hardware capabilities that enable control algorithm execution in more realistic settings. In PIL, the target processor operates in a non-real-time environment, communicating with external processors through capabilities installed on the host PC in a simulated integrated environment. PIL requires drivers to link the computer platform to relevant hardware. The generated object code is downloaded to an off-the-shelf evaluation board equipped with the target processor, where it integrates with test-management tools. The PC-based simulation tool communicates with the downloaded program via a serial communication channel, sending test values and awaiting processor responses.

The HIL (Hardware-In-The-Loop) test evaluates software real-time functionality, which PIL cannot accomplish. While this may appear limiting, it allows splitting the simulation problem into two verifiable sections before confirming correct controller firmware operation on an independent processor platform. PIL facilitates compiler optimization evaluation on a non-real-time execution platform using off-the-shelf processor architectures. HIL represents the final embedded controller system development phase, requiring electrical emulation of sensors and actuators on a real-time target platform before validating the controller with actual plant components. These electrical emulations connect plant simulation with the evaluated embedded system, with the plant simulation modifying electrically reproduced sensor values that the embedded system interprets, providing real-time feedback analogous to pre-installation conditions.

This work aims to employ an effective PZR system model combining various PZR dynamic characteristics and PC-influenced parameters suitable for control applications. A MIMO pressure and level control system using standard PID controllers is concurrently developed and implemented for the nonlinear two-region PZR model. However, constant PID gains prove unsuitable for setpoint variation scenarios. Therefore, an adaptive PID (APID) controller based on fuzzy logic is applied for pressure and level control of the nonlinear PZR model. The APID algorithm selection is based on its tracking speed, steady-state performance, and implementability on integrated boards, ensuring robustness. Each PZR unit controller is implemented and evaluated through PIL for different operation scenarios. The PZR model is implemented in MATLAB/Simulink with setpoint changes to study robustness. Simulation results demonstrate that the proposed APID controller outperforms conventional PID. The STM32F407 discovery kit executes PIL simulation for the proposed controllers connected to the PZR model. Required drivers facilitate hardware-computer platform communication (PIL). The generated object code links with test-management functionality and downloads to the board. A serial link communicates the downloaded software with the laptop-based simulation tool, connecting the PZR simulation model with the STM32F407 discovery kit system via serial communication protocol.

Furthermore, software development and validation tools must meet DO-178C standards, making MATLAB/Simulink a qualified tool [23, 24]. The remainder of this paper is organized as follows: Section 2 describes the pressurizer model, Section 3 derives PZR pressure and water level control strategies, Section 4 studies adaptive PID-based fuzzy logic control for the PZR system, Section 5 illustrates the proposed adaptive PID controller applied to different MIMO pressurizer operation scenarios, and Section 6 presents PIL implementation of the adaptive PID controller for PZR pressure and water level under various scenarios, comparing results with simulation outcomes.

II. Pressurizer Model Description

Although many mathematical models describe pressurizer operation, including three, four, and multi-region models [2, 25, 26], these models did not derive relationships describing the PZR surge line flow rate with the primary circuit. Therefore, this work employs a two-region model that establishes a mathematical relationship for the surge line equation. Based on the nonlinear two-region PZR model equations from [10], which demonstrate good performance in predicting PWR pressurizer dynamic behaviors across wide operational transients, the model is expressed by a set of ordinary differential equations in (1). The mathematical modeling divides the PZR into two regions—steam and water—connected to the PC heat pipe section through the surge line (hot leg). Fig. 1 [Figure 1: see original paper] illustrates the different PZR areas and divisions, showing the unit' s thermodynamic processes.

The PZR model is divided into three stages: inputs, states, and outputs. The input stage builds all PZR inputs, while the intermediate stage consists of five states representing: (1) steam mass inside the PZR, (2) water mass change inside the pressurizer, (3) primary circuit water mass, (4) PZR water temperature, and (5) PZR steam temperature.

PWR load power changes require corresponding pressure adjustments. Heater and spray operation scenarios relate to pressure, which associates with surge line water flow in/out of the PZR. The surge flow rate is derived by equation (2), depending on PC coolant average temperature, hot leg temperature, coolant inlet/outlet mass flow rates, reactor power, steam generator temperature, PC inlet temperature, and PC power loss. These parameters affect PZR operation by increasing or decreasing PWR pressure, reflected in load power changes.

III. Pressurizer Control System

PZR pressure is typically managed through spray flow rate and electrical heater power, adjusted via control signals based on pressure error input. This controller is commonly called a pressure error controller. To maintain PZR water level at its operating point, the inlet flow rate must be regulated. Fig. 2 [Figure 2: see original paper] shows the block diagram for controlling both PZR pressure and level using a cascaded flow rate error controller system with constant output flow rate.

PZR electrical heaters are classified into two groups: one bank of variable heaters and several banks of backup on/off heaters. Variable heater applied voltage adjusts heat output across a pressure range, maintaining equilibrium heat balance during steady-state conditions. For significant pressure decreases from the setpoint, variable heaters provide maximum output while backup heaters activate. All heaters turn off when PZR pressure exceeds the setpoint. Spray valves open across a fixed pressure range, allowing cooler water to condense steam and return pressure to nominal values.

In process control systems with significant system responses, pressure, level, and flow rate error controllers must tune their parameters to achieve satisfactory PZR control performance. Fig. 3 [Figure 3: see original paper] illustrates the schematic diagram for PZR pressure control [8].

For water level control, level decreases during RCS leakage or average temperature reduction, reflected in increased steam volume (out-surge), reduced steam temperature, and decreased steam/system pressure. Conversely, decreasing steam volume (in-surge) increases water level, steam temperature, and both steam/system pressure. The PZR level is adjusted by controlling charging pump flow rate: decreasing level is treated by increasing inlet flow beyond outlet flow, while increasing level is treated by reducing inlet flow below outlet flow. The water level error signal controls PC inlet flow rate, with the control objective being dynamic controller design for PZR level and pressure.

The control signal (inlet mass flow rate to the PC) required to maintain PZR water level at the desired reference value is derived in equation (3).

IV. Adaptive PID Based Fuzzy Logic Controller Design for Pressurized System

The PID controller is widely used in engineering control across various sectors, comprising three terms: proportional (P), integral (I), and derivative (D). The difference between reference setpoint and measured signal feeds into the PID controller, with output determined by the mathematical formula: u(t) = k e(t) + k e(τ)dτ + k de(t)/dt. The error signal e(t) represents the difference between setpoint and plant output, with PID parameters influencing system dynamics. Closed-loop step response is assessed through four main characteristics: (1) proportional controller (K) reduces rise time and steady-state error (without elimination), (2) integral controller (K) eliminates steady-state error but worsens transient response, (3) derivative control (K) increases stability, reduces overshoot, and improves transient response, and (4) PID controller disadvantages include constant control coefficients (k , k , k) that remain fixed throughout the control process.

PZR system complexity and multivariable conditions render conventional PID-based control solutions unsatisfactory. To improve control performance, these coefficients may require time-varying adjustment. Fuzzy controllers leverage typical methods' robustness and reliability in power systems to resolve diverse control problems. Fuzzy logic employs linguistic rather than numerical variables, requiring combination of multiple artificial intelligence concepts for effective control system creation. A fuzzy logic controller (FLC) can replace PID controllers when system models are inaccessible or imperfect.

The adaptive PID (APID)-based fuzzy logic controller addresses this by allowing PID coefficients to vary with time based on conditions. Using error and error derivative data as fuzzy system inputs, the FLC can alter k , k , and k values at any instant, enabling APID controller output to follow reference signals more effectively than traditional PID controllers.

A Mamdani-type fuzzy system adjusts PID coefficients, providing compensators based on intuitive user understanding without requiring mathematical models. Mamdani fuzzy controllers consist of four main components: fuzzifier, inference system, knowledge base, and defuzzifier (Fig. 4 [Figure 4: see original paper]). The fuzzifier converts computed process quantities (pressure error/error derivative and level error/error derivative) into fuzzy sets for the inference system, which delineates the link between FLC input and output. The knowledge base contains vague "if-then" rules describing expert tool handling. The inference process, the fuzzy control system' s brain, simulates expert decision-making through approximate inference following the intended control policy [27]. This involves two tasks: (1) matching—determining whether each fuzzy rule from the knowledge base fits present input conditions, and (2) inference—deriving conclusions (reaching suitable control signals) from knowledge-input bases and facts.

The defuzzifier converts the inference mechanism' s fuzzy output into crisp control actions applicable to the dynamical system. Common defuzzification approaches include center of gravity (COG) and center average (CA). This article utilizes the COG method. The PID control system with fuzzy gain scheduler (Fig. 4 [Figure 4: see original paper]) alters controller coefficients using fuzzy rules and reasoning [28], with PID controller operational response specifying required proportional, derivative, and integral gains.

FLC is based on fuzzy control rules for linguistic variables of the form: IF (error is A) AND (error derivative is B) THEN (output is C). Tables (2)-(4) illustrate fuzzy rules for adjusting proportional gain (δk), integral gain (δk), and derivative gain (δk), respectively. Membership functions are named S3, S2, S1, M, P1, P2, and P3, where S, M, P represent small, medium, and big, respectively.

The proposed APID controller uses a two-level structure: the fuzzy network as the first level and the PID controller as the second. PID controller gains are tuned for each control area, with controller gains (δk , δk , δk) estimated based on error and error change. These estimated gains feed into the PID controller to calculate new K , K , and K values, where the output values after tuning combine with starting PID controller values.

While various control devices can theoretically apply to PZR systems, practical implementation requires different processes between simulation and hardware. The V-cycle development process for embedded applications [18, 19, 29] typically employs MIL, SIL, and PIL tests. The next section applies the proposed APID controller through processor-in-the-loop work to validate its viability for PZR systems.

V. Processor in the Loop Implementation for the Proposed Scheme

The proposed controller with fixed step sample time (0.5 sec) is modeled and connected to the PZR model. The controller model undergoes MIL testing in the simulation environment (Simulink), where controller and plant models are simulated on the host computer without hardware components [30-32]. The second step creates SIL by generating software from the host computer model. The third step involves PIL generation (Fig. 5 [Figure 5: see original paper]).

After MIL validation, SIL automatically checks code from the control model. In SIL testing, 64-bit target code is generated from the model using Microsoft Windows SDK and embedded coder tools, validated on the host computer without additional hardware [30]. The "Create Software-in-the-Loop (SIL) block" option must be selected before constructing the fixed-stage controller model. Simulink' s S-function block executes the generated code, linking it to the PZR model, with results compared to MIL test outcomes.

Following SIL validation, PIL examines dynamically generated embedded software and assesses controller implementation. Code is generated for the embedded target, with the hex file loaded and run on the embedded board using the target' s compiler and embedded coder function, while the host computer simulates the plant model. Connection occurs via USB cable. PIL testing is fundamental to production as it ensures implementation code meets approach criteria [33]. The embedded board used is the STM32F4 Discovery board from ST Microelectronics, integrating the STM32F407VG microcontroller with a 32-bit ARM Cortex-M4F CPU and 1 Mbyte flash memory.

VI. Results and Discussion

This section presents the PZR model developed in MATLAB/Simulink with various input variables, solved using the Simulink fixed-step ode45 solver for the nonlinear two-region model. The proposed APID controller performance considers PWR load power variation, with controllers designed based on the nonlinear PZR system dynamic model. Three scenarios are examined: regular reactor operation, loss of reactor coolant flow rate, and PZR pressure setpoint change. Output behavior is analyzed and validated using input data from Table (5).

The Matlab PID Tuner Toolbox tunes PID controllers for level and pressure, obtaining proportional, integral, and derivative gains that are applied to record step responses for each group.

A. Regular Operation with 100% Load Power

PID and APID controllers are first applied at full load power (100%). The PZR water level response (Fig. 6 [Figure 6: see original paper]) shows damping oscillation around the 11 m reference level. The pressure response comparison around the 162 bar setpoint (Fig. 7 [Figure 7: see original paper]) reveals that the traditional PID controller fails to rapidly settle pressure at its 162 bar target, maintaining steady-state error for 500 sec settling time with 47.6% overshoot and 6 sec rise time using constant gains K = 0.28, K = 0.01, and K = 0.7.

The APID controller achieves lower steady-state error with 400 sec settling time, improving overshoot to 9.34% with 7.7 sec rise time (Table 6). The superior APID pressure response features appropriate spray and heater actuation (Figs. 10-11) synchronized with control signals (Fig. 9) and adapted gains k_1, k_1, k_1 (Fig. 12(b)). The PID water level response (Fig. 6) shows damping oscillation around 11 m, fluctuating between -0.6% and 0.7% with 3.735 sec rise time (Table 7). Spray and heater actuation (Figs. 10-11) synchronize with control signals (Fig. 8) using constant gains K_2 = 99990.65, K_2 = 89000.004, and K_2 = 7000.7. The APID water level response (Fig. 6) achieves 0.5% overshoot and

4.5 sec rise time with adapted gains k $_2$, k $_2$, k $_2$ (Fig. 12(a)), demonstrating APID superiority in both overshoot and rise time performance.

B. Normal Operation with Load Power Variation

Load power varies between 100%, 80%, 40%, and 60% over 1200 seconds (Fig. 13 [Figure 13: see original paper]). The PID water level response (Fig. 14 [Figure 14: see original paper]) shows damping oscillation around 11 m with 49 sec rise time, 10.6% overshoot, and -0.09% undershoot using constant gains K $_2$ = 9999.65, K $_2$ = 89000.1, and K $_2$ = 7000.7. Spray and heater actuation (Figs. 18-19) synchronize with control signals (Fig. 16). The APID water level response (Fig. 15) shows improved performance with adapted gains (Fig. 20(a)).

The PID pressure response (Fig. 15 [Figure 15: see original paper]) fails to rapidly settle at 162 bar, maintaining steady-state error with 5.4 sec rise time, 86.7% overshoot, and -86.7% undershoot using K = 0.38, K = 0.01, and K = 0.4. The APID controller improves overshoot to 4.9% and undershoot to 10.5% with 11.5 sec rise time (Table 9), demonstrating superior pressure control with excellent spray and heater actuation (Figs. 18-19) synchronized with adapted gains k $_1$, k $_1$, k $_1$ (Fig. 20(b)).

C. Loss of Reactor Coolant Inlet Flow

The PWR VVER-1200 simulator is subjected to reactor coolant inlet flow loss malfunction as detailed in [36, 37]. Reactor coolant pumps (RCPs) provide the pressure head for forced coolant circulation. Tripping one or more RCPs rapidly raises fuel temperature due to lower coolant flow rate under typical conditions, reducing reactor output by approximately 30% (Fig. 21 [Figure 21: see original paper]). The reactor protection system autonomously initiates a reactor trip, followed by a turbine trip. After shutdowns, negative flow rate in the RCP signifies flow direction reversal.

Manual RCP deactivation increases average PC temperature T g due to reduced coolant circulation, diminishing heat dissipation from the core. Without control rod action, reactor output declines by approximately 30% within 10 seconds after RCP trip. Decreased cooling flow reduces moderation, while increased T g introduces negative reactivity from the negative moderator temperature coefficient. The low coolant flow rate triggers a reactor trip alert within 10 seconds, typically followed by turbine trip. Natural circulation gradually develops, removing residual core heat.

When coolant flow changes in loop-B, the flow rate becomes negative (Fig. 22 [Figure 22: see original paper]), and the cold-leg temperature exceeds the hot-leg temperature. Figure 23 [Figure 23: see original paper] illustrates coolant temperatures in the loop where the RCP was activated. Initial hot-leg temperature decrease results from diminished core power, while cold-leg temperature increase reduces coolant pressure flow. After approximately 10 seconds, the reactor trip causes rapid cold-leg temperature drop. Hot-leg temperature rises slightly after 30 seconds due to heat of oxidation, then rapidly drops after 40 seconds from backflow. After 60 seconds, backflow causes cold-leg temperature to exceed hot-leg temperature.

The surge flow rate generated by RCS coolant swelling and shrinkage during transients is computed using PCtran VVER-1200 simulator data (Fig. 24 [Figure 24: see original paper]). The nonlinear PZR model with various APID controller settings is subjected to these conditions per equation (1).

The conventional PID controller fails to quickly settle pressure at 162 bar, maintaining 97.8% overshoot with 1.83 sec rise time using constant gains K = 0.28, K = 0.1, and K = 0.7 (Fig. 26 [Figure 26: see original paper]). Spray and heater actuation (Figs. 29-30) synchronize with control signals (Fig. 28). The APID controller achieves lower steady-state error with 9.34% overshoot and 4 sec rise time (Table 10), demonstrating superior pressure control with adapted gains k_1, k_1, k_1 (Fig. 31(b)). The PID water level response shows 54% overshoot and 34% undershoot (Fig. 25 [Figure 25: see original paper], Table 11) with constant gains K_2 = 9999.65, K_2 = 8900.004, and K_2 = 7000.7. The APID water level response achieves 1.7% overshoot with adapted gains k_2, k_2, k_2 (Fig. 31(a)), confirming APID superiority in both overshoot and rise time performance.

D. First Scenario for Setpoint Change

The operating point changes from 162 bar to 150 bar pressure and 11 m to 8 m water level to compare APID and PID controller reactions. System responses are shown in Figs. 32 [Figure 32: see original paper] through 38 [Figure 38: see original paper].

The PID water level response (Fig. 32) changes from 11 m to 8 m with -0.7% overshoot, 0.7% undershoot, and 4 sec rise time (Table 12) using constant gains K_2 = 28330, K_2 = 234.5, and K_2 = 2320. The APID water level response achieves 0.4% overshoot and 4.5 sec rise time with adapted gains (Fig. 38(a)), demonstrating APID superiority in overshoot and comparable rise time.

The PID pressure response (Fig. 33 [Figure 33: see original paper]) fails to quickly settle at 162 bar, maintaining steady-state error for 100 sec settling time with -0.5% overshoot and 2.129 sec rise time using K = 0.26, K = 0.01, and K = 0.09. Spray and heater actuation (Figs. 36-37) synchronize with control signals. The APID controller achieves lower steady-state error with -0.4% overshoot and 1.8 sec rise time (Table 13), demonstrating superior pressure control with appropriate spray and heater actuation synchronized with adapted gains k_1, k_1, k_1 (Fig. 38(b)).

E. Second Scenario for Setpoint Change

The operating point changes from 162 bar to 150 bar then back to 162 bar pressure, and from 11 m to 8 m then back to 11 m water level to evaluate controller reactions. System responses are shown in Figs. 39 [Figure 39: see original paper] through 45 [Figure 45: see original paper].

The PID and APID water level responses (Fig. 39 [Figure 39: see original paper]) show level changes with overshoot, undershoot, and rise times listed in Table 14. The PID controller uses constant gains $K_2 = 28330$, $K_2 = 234.5$, and $K_2 = 2320$, while APID uses adapted gains (Fig. 45(a)), demonstrating APID superiority in overshoot and comparable rise time.

The PID pressure response (Fig. 40 [Figure 40: see original paper]) fails to quickly settle at 162 bar, maintaining steady-state error with rise time listed in Table 15. Spray and heater actuation (Figs. 43-44) synchronize with control signals using constant gains $K = 0.26$, $K = 0.01$, and $K = 0.09$. The APID controller achieves lower steady-state error with improved overshoot and rise time (Table 15), demonstrating superior pressure control with appropriate spray and heater actuation (Figs. 43-44) synchronized with adapted gains k_1, k_1, k_1 (Fig. 45(b)).

VII. Conclusion

This work provides an extensive analysis of adaptive PID-based fuzzy logic controller design and implementation for pressurizer systems in Pressurized Water Reactors. The proposed control system regulates both pressure and water levels, addressing the nonlinear MIMO characteristics of the pressurizer. Validation through PIL testing on the STM32F407 discovery kit demonstrates practical usefulness. The controller and PIL implementation are validated using a non-equilibrium two-region PZR model with critical thermodynamic processes. PZR pressure is controlled via spray valve operation and electric heaters, while water level is controlled through primary circuit inlet flow rate. PID and adaptive PID-based fuzzy logic controllers are applied for constant and changing set-points. PIL implementation for pressure and level control shows that the adaptive PID controller efficiently improves PZR water level response and pressure performance compared to traditional PID controllers.

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