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MODELING AND CONTROL OF A NUCLEAR POWER PLANT USING AI TECHNIQUES

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ABSTRACT

In pressurized water reactor (PWR) nuclear power plants (NPPs) pressure control in the primary loops is fundamental for keeping the reactor in a safety condition and improve the generation process efficiency. The main component responsible for this task is the pressurizer. The pressurizer pressure control system (PPCS) utilizes heaters and spray valves to maintain the pressure within an operating band during steady state conditions, and limits the pressure changes during transient conditions. Relief and safety valves provide overpressure protection for the reactor coolant system (RCS) to ensure system integrity. Various protective reactor trips are generated if the system parameters exceed safe bounds. Historically, a proportional-integral-derivative (PID) controller is used in PWRs to keep the pressure in the set point, during those operation conditions. The purpose of this study is to develop fuzzy controllers for the PWR pressurizer modeled by an artificial neural network (ANN) and compare their performance with conventional ones. Data from a 2785 MWth Westinghouse 3-loop PWR simulator was used to test both the conventional and the fuzzy controllers. The simulation results show that the fuzzy controllers have better performance compared with conventional ones.

1. INTRODUCTION

Nuclear power plants are nonlinear systems in nature, with many complex components. They are difficult to model due to their parameters dependence on the time-varying power level. Many diverse models have been developed to represent the dynamic response of such systems. Computer simulation of the behavior of complex systems and components, which requires the solution of many equations and extensive use of closure relations, has become very important in modern design. This way of proceeding is used particularly in the nuclear industry where safety rules are rather rigid and require the close examination of any possible system condition and operational mode. In the phase of implementation of the physical-mathematical model, the discretization of the differential equation systems usually raises complex issues of stability and convergence of the solution process. Artificial neural networks (ANNs) can be used in this context to overcome this problem thanks to their ability in performing functional mappings. Akkurt and Çolak [1] have modeled several components of a PWR reactor using feedforward neural network. Oliveira and Almeida [2] have applied feedforward feed back ANN to model the pressurizer of a PWR simulator reactor.

Likewise, controlling the nuclear power plants systems is difficult due to their complex, time varying and insufficiently known parameters. The application of intelligent systems including fuzzy logic in the control of large-scale complex nonlinear systems as nuclear plants are very promissing. Fuzzy control scheme has been applied by Bhatt *et al.* [3] for generating regulating signals to feed and bleed control valves, which are used in Liquid Zone

Control System for maintaining constant pressure difference between gas outlet header and delay tank. Liu *et al.* [4] have applied a fuzzy proportional-integral-derivative (fuzzy-PID) controller in the nuclear reactor power control system tuned by genetic algorithm (GA).

The purpose of this work is to develop fuzzy controllers, tuned by GA, for a PWR pressurizer and compare their performance with conventional controllers.

2. PRESSURIZER MODEL BASED ON ARTIFICIAL NEURAL NETWORKS

In this work, the pressurizer modeled by ANN is described in Oliveira and Almeida (op. cit.), where the ANN is a feedforward backpropagation type using as training the scaled conjugate gradient (SCG), developed by Moller [5]. Fig. 1 shows the simplified pressurizer model used in the former work to model the pressurizer by ANN.

In order to compare the performances between the conventional and the fuzzy PID controllers, it was necessary to acquire the variables data set from the plant simulator necessary to model the pressurizer with a ANN, for both transient and stead-state conditions, see Fig. 2. Due to this, the implemented pressurizer model could be used to test both controllers types with the same input data set.

Fig. 3a shows the ANN architecture used with 19-13-1 neurons (n_i=19 inputs, n_h=13 hidden and n_o=1 output). As we can see the pressure is fed back as one input to the ANN in time $t\text{-}\Delta t$, making the ANN works as a recurrent network. Notice that, in order to take into account the actual time evolution of the other input variables, the ANN is provided for they with the values in time t, $t\text{-}\Delta t$ and $t\text{-}2\Delta t$, so that it can distinguish among situations in which the variables are increasing, decreasing or constant. In the training phase no feedback was used for the pressure variable, i.e., we use the data set showed in Fig. 2 as inputs/output. Learning was initiated by assigning random weights between -1 and 1. The learning rate and the momentum coefficient used during the training phase were α=0.6 and η=0.8, respectively. Fig. 3b shows the obtained results after the training phase for the same data set but with ANN feed back.

3. PRESSURIZER PRESSURE CONTROL SYSTEM

The block diagram of the PPCS is presented in Fig. 4a. The PPCS is composed by the fuzzy or classical PID controller block, witch receive as main input the error signal ε and supply as output the signal $f(\varepsilon)$. The controller output signal $f(\varepsilon)$ is added to the *Setpoint* value in order to shift the signal to the operation range of the actuators (heaters and spray) before to be applied to the input of the actuator block. The output signals from the actuator block (the heaters and spray signals) are sent to the correspondent inputs of the plant (the ANN pressurizer model) to control the pressure in the desired *Setpoint*. The pressure signal is fed back to the input sum block in order to obtain the error signal ε. In stead-state condition the error ε between *Setpoint* and pressure should be near zero. If some unbalance condition is achieved, for example a transient, causing an increase in the error, heaters or spray are actuated, depending on the direction of the error. In this case, the controller output signal $f(\varepsilon)$ starts the actuation system in order to compensate the pressurizer pressure.

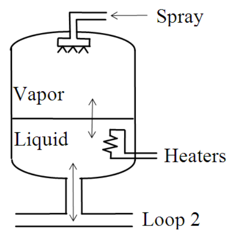


Figure 1: Pressurizer model.

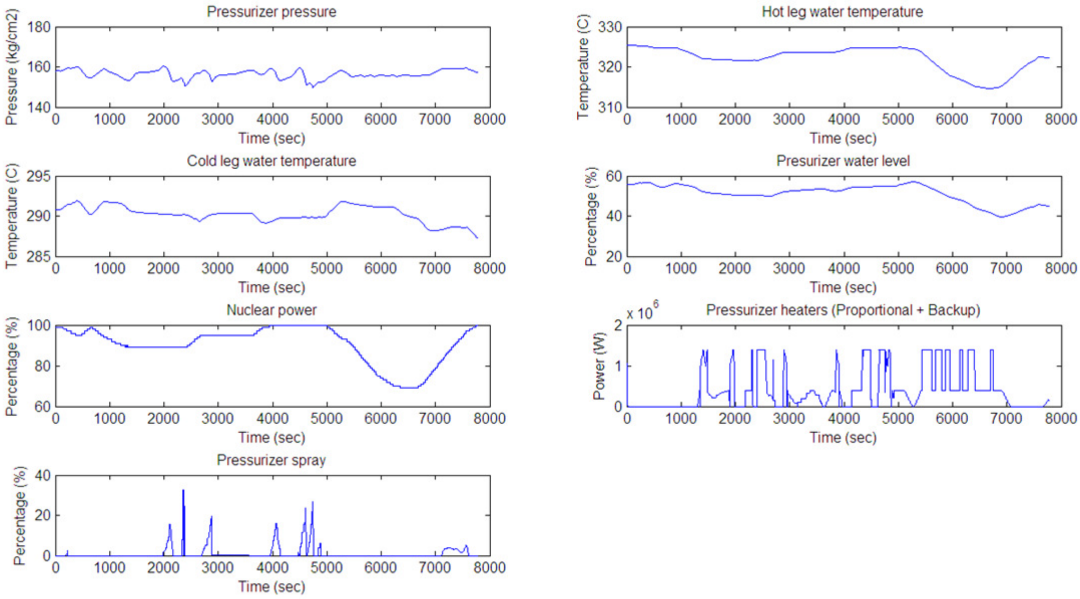


Figure 2: ANN training and testing patterns.

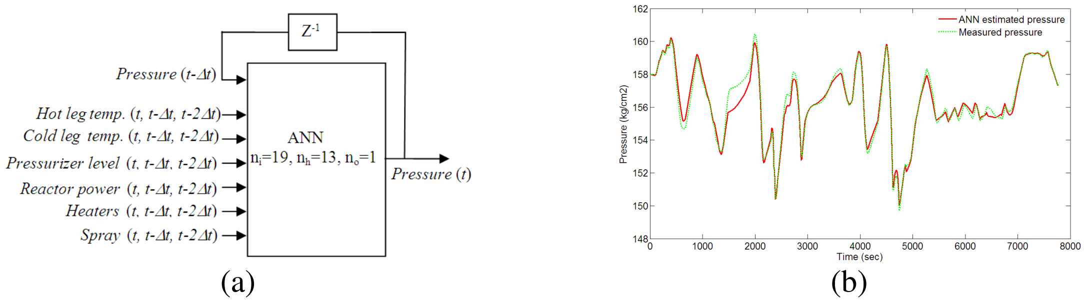
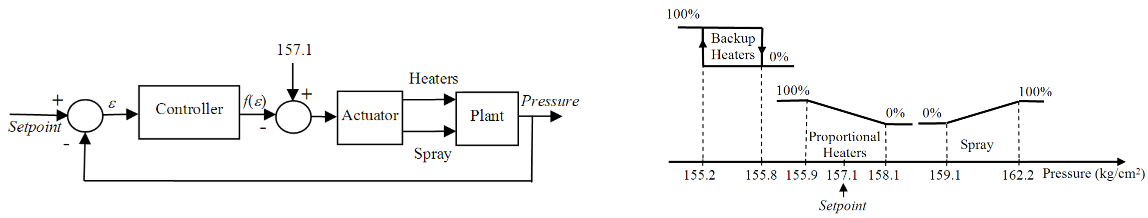


Figure 3: (a) ANN architecture; (b) Pressure results measured and estimated by the ANN.

The plant actuators, heaters and spray, are used to control the pressure in the pressurizer. This process can be understood as follows. First recall that at normal pressure, 157.1 kg/cm^2, the system is stable with the variable heater on at half capacity, compensating for ambient heat losses. For this reason a sum block is used to add this value to the controller output value, $f(\varepsilon)$, in order to shift this value to the plant actuators *Setpoint*, see Fig. 4a. Fig. 4b shows the span action of the electric heaters (proportional and backup) and cold water spray. If ε becomes positive the heaters should be actuated for increasing the pressure. In the same way, if ε is negative then spray valves should be opened for reducing the pressure. Secondly, if ε is large then spray valves should be opened to large value and vice versa. In the reference plant, 100% of backup and proportional heaters correspond to 1 MW and 400 KW of electric power, respectively.



(a) (b)

Figure 4: (a) Plant control diagram; (b).Controls action interval according with pressure *P*.

4. CONVENTIONAL PID CONTROLLERS

A PID controller is a generic control loop feedback mechanism widely used in industrial control systems. A PID controller calculates an error value ε as the difference between a desired *Setpoint* and a measured process variable (PV). The controller attempts to minimize the error by adjusting the process control inputs. The PID algorithm involves three separate parameters: the proportional, the integral and derivative values, denoted P, I, and D. Heuristically, these values can be interpreted in terms of time: P depends on the present error, I on the accumulation of past errors, and D is a prediction of future errors, based on current rate of change. The weighted sum of these three actions is used to adjust the process via a control element such as the position of a water spray control valve or the power supply of a heating element.

Defining $u_{PID}(k)$ as the controller output in discrete form, the PID algorithm is given by

$$u_{PID}(k) = K_p\left(\varepsilon(k) + \frac{1}{T_i}\sum_{i=1}^{k}\varepsilon(k)T_s + T_d\frac{\varepsilon(k)-\varepsilon(k-1)}{T_s}\right) \quad (1)$$

where the tuning parameters are K_p , T_i and T_d, the proportional gain, the integral time and the derivative time, respectively; ε is the error (ε = *Setpoint* - PV), T_s the sampling period, and k is the time step.

4.1. Tuning The Conventional PID Controller

Ziegler and Nichols [6] described simple mathematical procedures, the first and second methods respectively, for tuning classical PID controllers. In this work, we use the second method to tune the classical PID controllers.

5. FUZZY PID CONTROLLERS

The fuzzy controllers can be divided in four major parts: fuzzification, rule base, inference engine and defuzzification.

The initial membership functions for the input and output signals of the fuzzy logic controllers in the PPCS test setup are described in the following. Genetics algorithms are used to tune the position and shape of theses membership functions in order to minimize the controller output error. This is described later on section 6.3.

Based on observation and experts experience, trapezoidal and symmetric triangles are used to convert the inputs ε and $\Delta\varepsilon$ into five linguistic terms. Trapezoidal are used for NL (negative large) and PL (positive large). Initially, symmetric triangles with equal base and 50% overlap with neighboring membership functions are used for NS (negative small), ZE (Zero) and PS (positive small). Fig. 5 shows the initial values used for each membership function. The universe of discourse of ε was chosen in the range [-10,10] and for $\Delta\varepsilon$ in the range [-1,1].

Based on observation and experts experience, singletons [7] are used to express the output pressure (P) into five linguistic terms: NL (negative large), NS (negative small), ZE (Zero), PS (positive small) and PL (positive large). Fig. 5 shows the initial position values used for each singleton. The output universe of discourse was chosen in the range [-6,6].

The P controller uses five if-then rules to control the pressure in the pressurizer given by
1. If ε is NL then P is NL
2. If ε is NS then P is NS
3. If ε is ZE then P is Z
4. If ε is PS then P is PS
5. If ε is PL then P is PL

For the PI controller the rule base can be imagined to be a two dimensional matrix as summarized in Table 1. The rows represent the various linguistic values that change of error, $\Delta\varepsilon$(k), can take and columns indicate the values of error ε(k). The entries in this matrix would be the control action that has to be taken described in the linguistic terms.

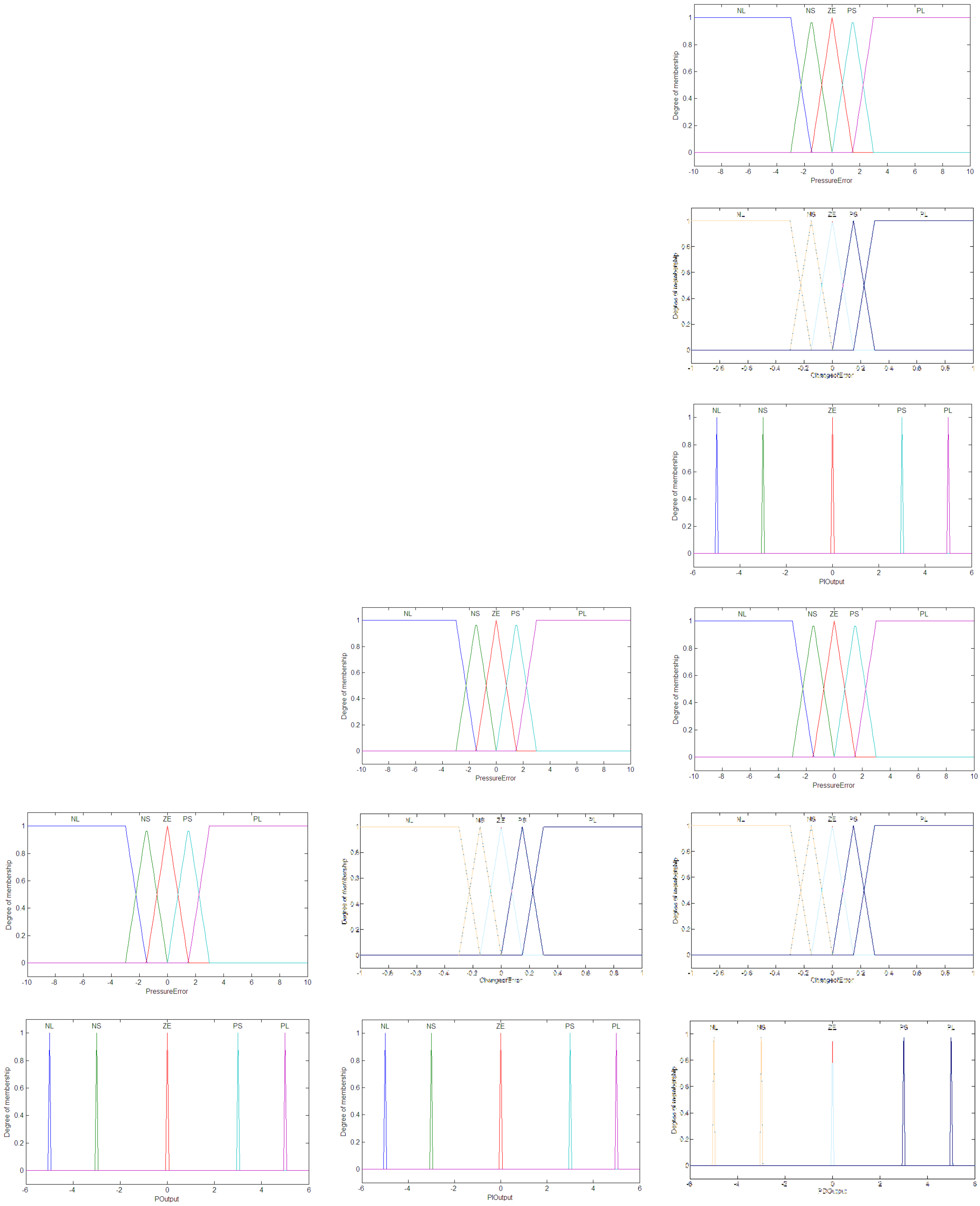
Table 1: Rule base for Fuzzy PI Controller.

		Change of error ($\Delta\varepsilon$)				
		NL	**NS**	**ZE**	**PS**	**PL**
Error (ε)	**NL**	ZE	NS	NL	NL	NL
	NS	ZE	ZE	NS	NS	NS
	ZE	PS	PS	ZE	NS	NS
	PS	PS	PS	PS	ZE	ZE
	PL	PL	PL	PL	PS	ZE

The Fuzzy PI+Fuzzy PD (fuzzy PID) has the same rule base used in the Fuzzy PI. Theoretically, the rule based should be different for Fuzzy PI controller and Fuzzy PD controller, but in order to reduce the complexity of design and to increase efficiency, a simple structure of Fuzzy PI+Fuzzy PD controller was used with a single rule base. A PI rule base was considered because PI controller is generally more important for steady state performance [8].

Mamdani inference method Prod-Max is used to infer the output contribution from each rule. Hence, prod operation is performed to implication operator and max operation is performed to aggregate the control outputs obtained as a result of firing several rules.

We use the Center of Maximum (CoM) defuzzification method. In CoM method the fuzzy logic controller first determines the typical numerical value for each scaled membership function. The typical numerical value is the mean of the numerical values corresponding to the degree of membership at which the membership function was scaled.



(a) (b) (c)

Figure 5: Initial inputs/outputs membership functions for: (a) P; (b) PI; (c) PI+PD.

5.1. Fuzzy Controllers Strategies

A conventional P controller is described in discrete form by Eq. (2). In the fuzzy P controller, the k_p parameter is dynamically adjusted depending on the process error value ε and can be expressed as the relationship between the output controller $u_p(k)$ and the input error ε(k). Fig. 6a shows the implementation of Fuzzy P controller.

$$u_P(k) = K_p \varepsilon(k) \tag{2}$$

A conventional PI controller is described in discrete form can be written as

$$\Delta u_{PI}(k) = k_p \Delta\varepsilon(k) + \frac{k_p}{T_i}\varepsilon(k) \tag{3}$$

where $\Delta\varepsilon(k) = \dfrac{\varepsilon(k) - \varepsilon(k-1)}{T_s}$, and $\Delta u_{PI}(k) = \dfrac{u_{PI}(k) - u_{PI}(k-1)}{T_s}$

In the fuzzy PI controller, the k_p and T_i parameters are dynamically adjusted depending on the process error ε and $\Delta\varepsilon$ values and can be expressed as the relationship between the output controller $u_{PI}(k)$ and the inputs error ε(k) and $\Delta\varepsilon$. Fig. 6b shows the implementation of Fuzzy PI controller.

A conventional PID controller in discrete approximation follows the control law given by Eq. (1). To implement the Fuzzy PID controller three inputs ε(k), $\Sigma\varepsilon$(k) and $\Delta\varepsilon$(k) are required. Increasing the number of input variables causes a rise in the dimension of the rule table and, therefore, in the complexity of the system; this makes its implementation more complicated. For this reason, a combination of Fuzzy PI+Fuzzy PD [9] controller was employed instead of three input Fuzzy PID controller.

A conventional PD controller is described in discrete form by equation

$$u_{PD}(k) = k_p \varepsilon(k) + k_p T_d \Delta\varepsilon(k) \tag{4}$$

where $\Delta\varepsilon(k) = \dfrac{\varepsilon(k) - \varepsilon(k-1)}{T_s}$.

In the fuzzy PD controller, the k_p and T_d parameters are dynamically adjusted depending on the process error ε and $\Delta\varepsilon$ values and can be expressed as the relationship between the output controller $u_{PD}(k)$ and the inputs error $\varepsilon(k)$ and $\Delta\varepsilon(k)$.

Finally, the overall Fuzzy PI+Fuzzy PD controller can be obtained by algebraically summing the Eq. (3) and Eq. (4). Fig. 6c shows the implementation of Fuzzy PI+Fuzzy PD controller.

5.2. Tuning The Fuzzy PID Controller

Fuzzy controllers are rule-based systems with many parameters that can be altered to optimize the controller performance. They are: the scaling factors for each linguistic variable, the fuzzy set representing the meaning of linguistic values, and the if-then rules. In this work, we present an adaptive fuzzy controller that tunes the scaling factors as well as the position and shape of the membership functions of each variable, using GA, where the chromosomes are represented by vectors real numbers.

5.2.1. Chromosome representation

Fig. 7a shows the chromosome alleles position for the fuzzy P controller. The chromosomes have a size of 10 alleles, C_1, C_2,…, C_{10}, to map the membership function of the fuzzy controller. The alleles correspond to the top vertices of each membership function. Fig. 8 shows the initial alleles position of each membership function for the P controller, where the domain of the input and output variable is defined in the range [-R, R] and [-S, S], respectively.

During the optimization phase, the position C_i of the allele i (the position of the top vertices of the membership i) is changed and, consequently, its shape. The triangular memberships are composed by 3-tuple (C_{i-1}, C_i, C_{i+1}), with $2 \leq i \leq 4$ and, normally, during the optimization process starts with symmetric triangular memberships to achieve an asymmetric configuration at the end. The trapezoidal ones by 4-tuple (-R, -R, C_1, C_2) and (R, R, C_4, C_5) for the left and right side, respectively. In the same way, the output memberships are simply singletons, using triangular membership functions with an infinitely small width. The vertices C_6 to C_{10} represent the position of each one, that will be tuned by the GA optimization. In our application, for both input and output variable, we fixed the vertices of the central membership functions in zero, i.e., the correspondents alleles are set to zero ($C_3 = C_8 = 0$) in the chromosome.

Fig. 7b shows the chromosome alleles position for the fuzzy PI controller. The chromosomes have a size of 15 alleles, C_1, C_2,…, C_{15}, to map the membership function of the fuzzy controller. The shape of the inputs are similar to described before, but the domain of the second variable is different. In the same way, the output memberships are simply singletons, as described above. Again, the vertices of the central membership functions are fixed in zero ($C_3 = C_8 = C_{13} = 0$).

Fig. 7c shows the chromosome alleles position for the fuzzy PI + fuzzy PD (PID) controller. The chromosomes have a size of 30 alleles, C_1, C_2,…, C_{30}, to map the membership function of the two fuzzy controllers. Similarly, the vertices of the central membership functions are fixed in zero ($C_3 = C_8 = C_{13} = C_{18} = C_{23} = C_{28} = 0$).

5.2.2. Fitness function

The fitness function used consists of two parts. The first is the sum of the controller error. In this work, to assess the fitness of each chromosome, we use the Integral of Time multiplied by Absolute Error (*ITAE*) given, in discrete form, by

$$ITAE = \frac{1}{n}\sum_{i=1}^{n} i\left|\varepsilon_i\right| \tag{5}$$

where ε is defined by the error between the obtained output *Pressure* and the plant *Setpoint*, and n is the total number of data sample. The *ITAE* weights the error with time and hence emphasizes the error values later on in the response rather than the initial large errors.

The second part consists of a penalty value that is applied to invalid individuals. The penalty function (P) is applied when an invalid chromosome (or individual) is produced by the GA process. When an individual has an inversion of an allele position with respect to other allele in any input or output of the chromosome, a penalty is generated. This means that the membership order is violated, i.e., the alleles allowed position, $C_1 < C_2 < \ldots < C_n$, is not satisfied, where n is the size of each input or output membership functions. For the left side of the input/output membership functions of each variable the penalty function of the allele *i* is defined by

$$\text{if } \frac{|C_i|}{\delta + |C_{i+1}|} - 1 > 0 \text{ then } P_i = 0; \quad \text{else } P_i = \left| \frac{|C_i|}{\delta + |C_{i+1}|} - 1 \right| \tag{6}$$

where δ ($\delta = R/50$) is defined as the minimal distance allowed between two adjacent alleles C_i and C_{i+1}, and i is the allele number. For the right side of the input/output membership functions of each variable the penalty function of the allele *i* is defined by

$$\text{if } \frac{|C_i| + \delta}{|C_{i+1}|} - 1 < 0 \text{ then } P_i = 0; \quad \text{else } P_i = \left| \frac{|C_i| + \delta}{|C_{i+1}|} - 1 \right| \tag{7}$$

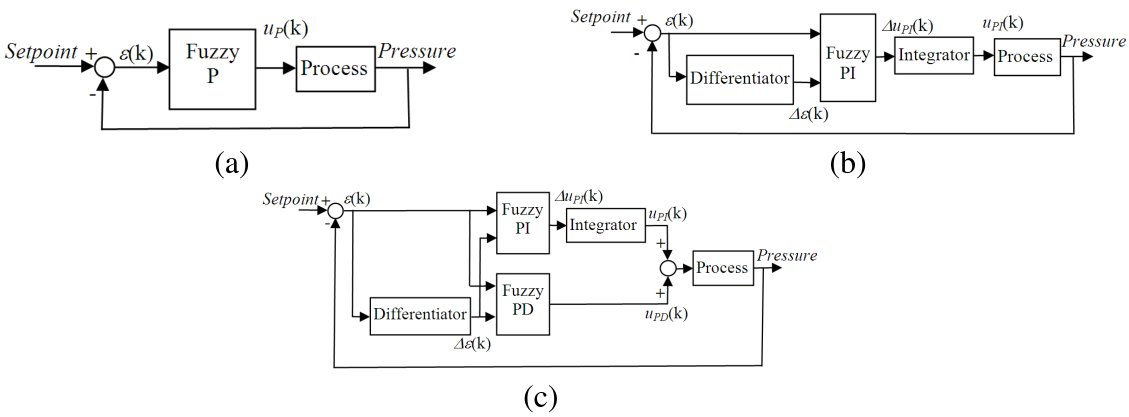


Figure 6: Pressure control for the fuzzy controller: (a) P; (b) PI; (c) PI+PD.

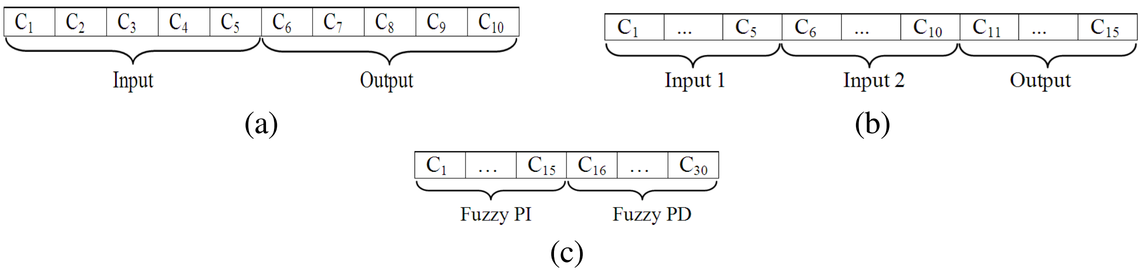


Figure 7: Chromosomes alleles for the fuzzy: (a) P; (b) PI; (c) PI+PD.

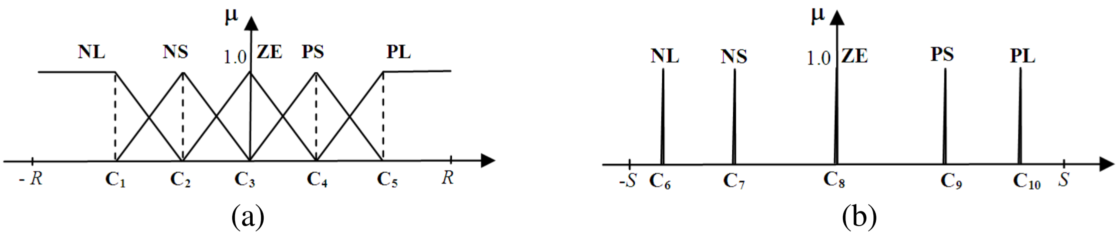


Figure 8: Alleles position of the membership functions for P controller for: (a) Input; (b) Output.

Another penalty function is used to control the maximum gain of the fuzzy P controller. This limitation avoids oscillation in the controller output and is given by

$$\text{if } \max\left|\frac{f(\varepsilon_i)}{\varepsilon_i+\sigma}\right| - g < 0 \quad \text{then } P_i = 0; \quad \text{else } P_i = \left|\max\left|\frac{f(\varepsilon_i)}{\varepsilon_i+\sigma}\right| - g\right| \tag{8}$$

where g is defined as the maximal allowed gain to the controller, σ is a small value added to avoid division by zero and i is defined in the interval $1 \le i \le N$, where N is the number of data sample.

Then, the assumed fitness function (F_c) for the c-th chromosome is given by

$$F_c = ITAE\left(1+\alpha\sum_{i=1}^{n} P_i\right) \tag{9}$$

where $\propto$ is weighting factor between the controller error and the penalties and n is the number of alleles in the chromosome.

6. RESULTS AND DISCUSSION

To compare the conventional controllers types with the correspondent fuzzy controllers types, the spans of the input variables, error (ε) and change of error ($\Delta\varepsilon$), and the output variable pressure (P) are limited to [-10, 10], [-1, 1], and [-6, 6], respectively. Out of these spans the controller system is considered saturated.

6.1. Tuning The Conventional Controllers

For tuning the conventional controllers it was used the Ziegler-Nichols second method. The same data set used to train the ANN model, see Fig. 2, was used to perform the tuning of the controller types. After applying the Ziegler-Nichols second method we obtained k_{cr}= 7.0 and P_{cr}= 5. Table 2 shows the correspondents gain values obtained for the three conventional controllers.

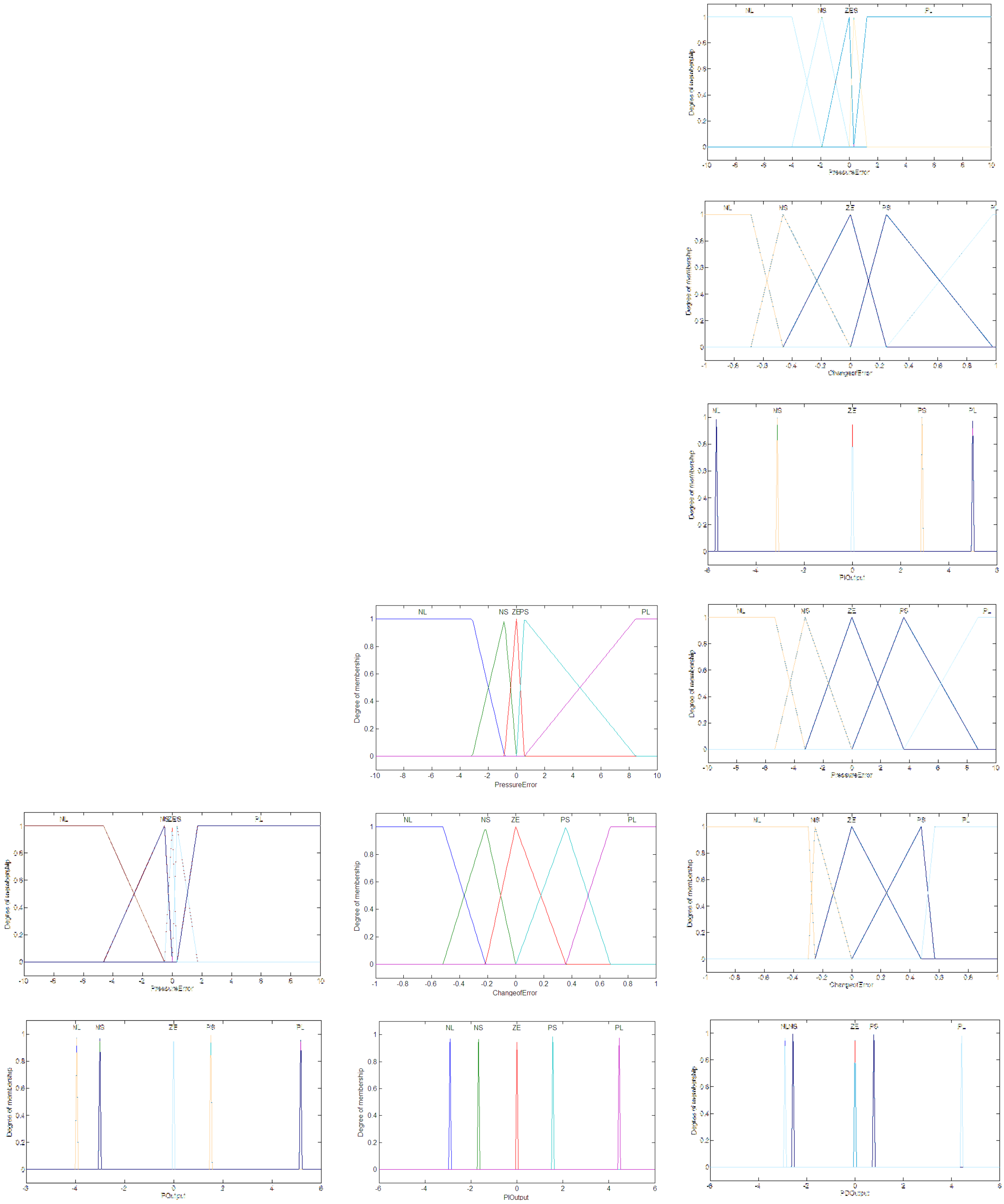
Table 2: Obtained values for Ziegler-Nichols second method.

Controller Type	K_P	T_i	T_d
P	3.5	∞	0
PI	3.15	4.17	0
PID	4.2	2.5	0.625

6.2. Tuning The Fuzzy PID Controllers

The parameters used in the GA optimization for tuning the fuzzy membership function of the PID controllers were set as follows: population size of 30; maximum number of generation of 25; uniform crossover with probability of 0.6; mutation probability of 0.02; and elitism (the best individual in the present generation is saved in the next generation).

The fuzzy P, PI and PID (PI+PD) controllers were tuned using the control structure showed in Fig. 4. As was said previously, we use as fitness function the Eq. (9) to evaluate each chromosome in the population. The weighting factor $\propto$ was set experimentally to 10, the maximum gain g was set equal to k_{cr} (g = 7.0) and the sigma factor was set to $\sigma = 0.01$. Fig. 9 shows the obtained shape of the membership functions for the fuzzy controllers after optimization.



(a) (b) (c)

Figure 9: Final inputs/output membership functions for: P; (b) PI; (c) PI+PD.

6.3. Results and Discussion

After tuning, the two controller were put to control the PPCS, as showed in Fig. 10. The output controlled variable pressure is fed back as one input to the ANN in time *t-Δt*. The control variables are changed by the controller block in order to stabilize the output pressure in its *Setpoint*. The plant operation variables are used to provide transients in the system. In our case, the reactor power is used to do transients in the range [60%, 100%].

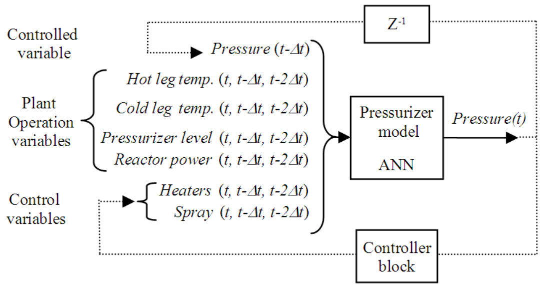


Figure 10: Control system inputs/output variables.

Fig. 11 to 16 show the systems response during these transients. In the figures, for the pressurizer pressure response, the continuous line represents the pressure *Setpoint* value and the upper and bellow dashed lines the values for spray and heaters actuations, respectively. As we can see in Fig. 11 and 12, the conventional P controller not settle the pressure at its target value, but retain a steady-state error. The fuzzy P controller presented lower steady-state error compared to the conventional one due to its adaptive gain. On the other hand, it is more sensitive (it stresses more the backup heaters actuator) due to its maximum gain of 5.6, obtained after GA optimization, that is bigger than the conventional proportional gain of 3.5. In general, the fuzzy PI presented better results compared to the conventional one, and both have similar actuation of spray and heaters, see Fig. 13 and 14. Fig. 15 and 16 shows the PID response for the two system. Although the derivative term slows the transient response of the controller, this term in the controller is highly sensitive to noise in the error term, and causes instability in the control process. The fuzzy PID controller seems to be more sensitive to noise in the error term compared to the conventional one. This can be seen mainly at the end of the samples (after 7000 sec) where the fuzzy PID response becomes a little unstable.

Table 3 summarizes the response of the two controllers types in terms of the *ITAE*. For all the systems, the *ITAE* obtained using fuzzy controllers showed relative reduction compared to the correspondent conventional ones.

Table 3: *ITAE* obtained for the controllers.

Controller	Conventional	Fuzzy	Error (%)
P	1856.7	1262.8	32.0
PI	460.7	405.1	12.0
PID	385.2	348.4	9.5

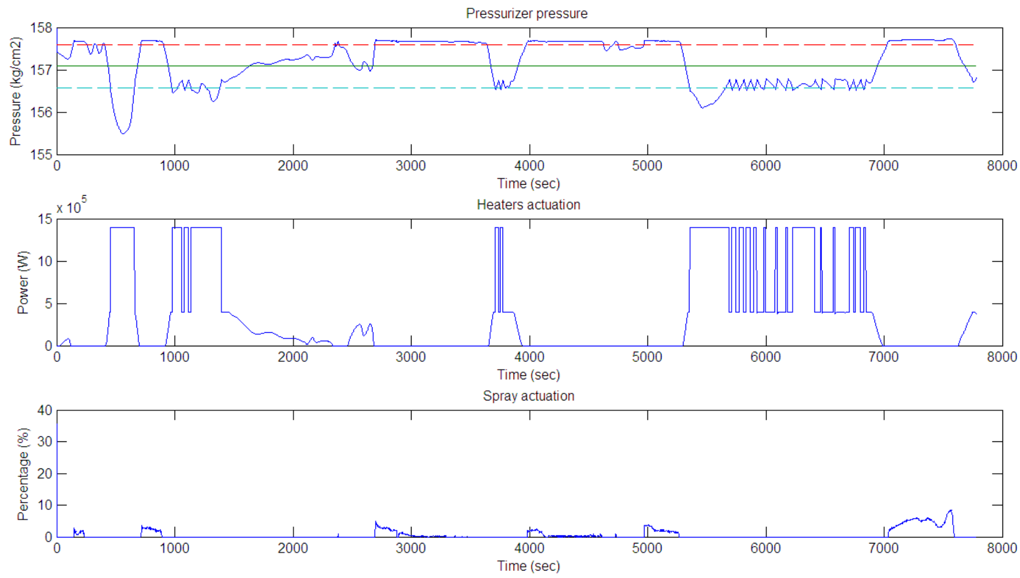


Figure 11. Conventional P controller response.

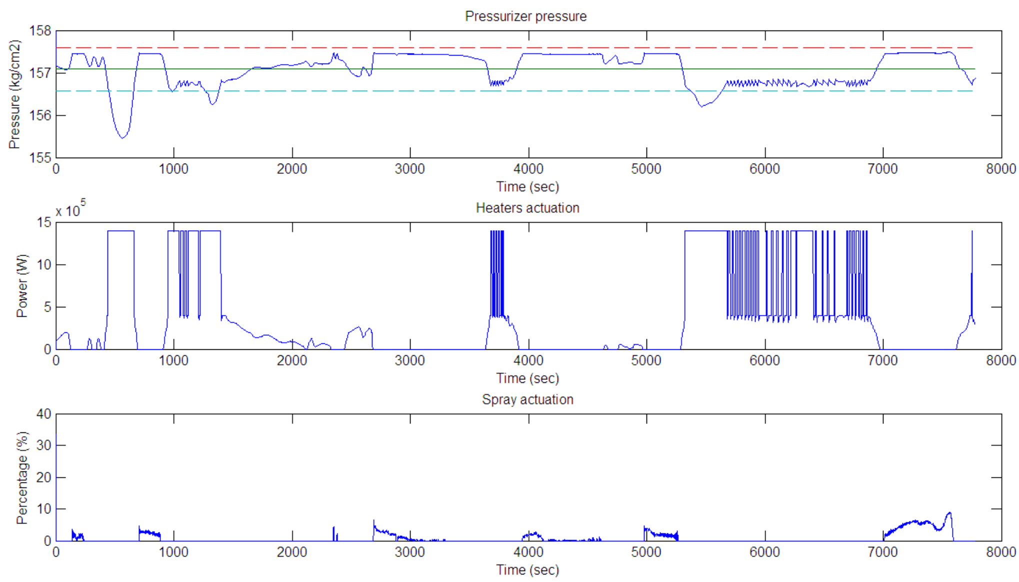


Figure 12: Fuzzy P controller response.

7. CONCLUSION

The control of nuclear power plants systems is difficult due to their complex, time varying and insufficiently known parameters. The application of intelligent systems including fuzzy logic in the control of large-scale complex nonlinear systems as nuclear plants have been applied recently. In this context, the goal of this work was to develop fuzzy controllers for the PWR pressurizer modeled by the ANN and to compare their performance with conventional ones. Both controller types were tested for transients in the nuclear power. Table 4 shows a relative reduction in the *ITAE* for the fuzzy controllers compared to the conventional ones. Probably, this is due to the intrinsic characteristic of the fuzzy controllers to adapt their gain with respect to the error changes.

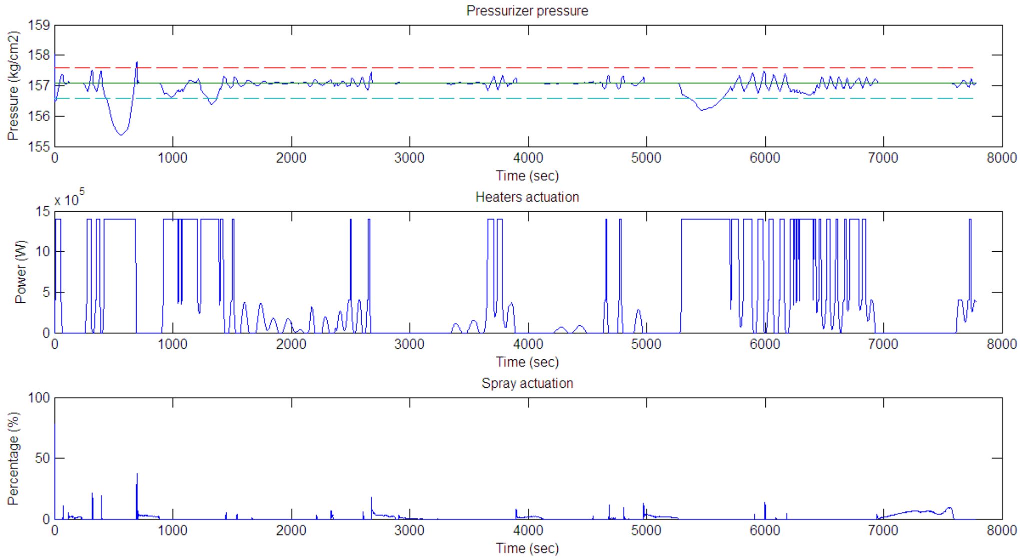


Figure 13: Conventional PI controller response.

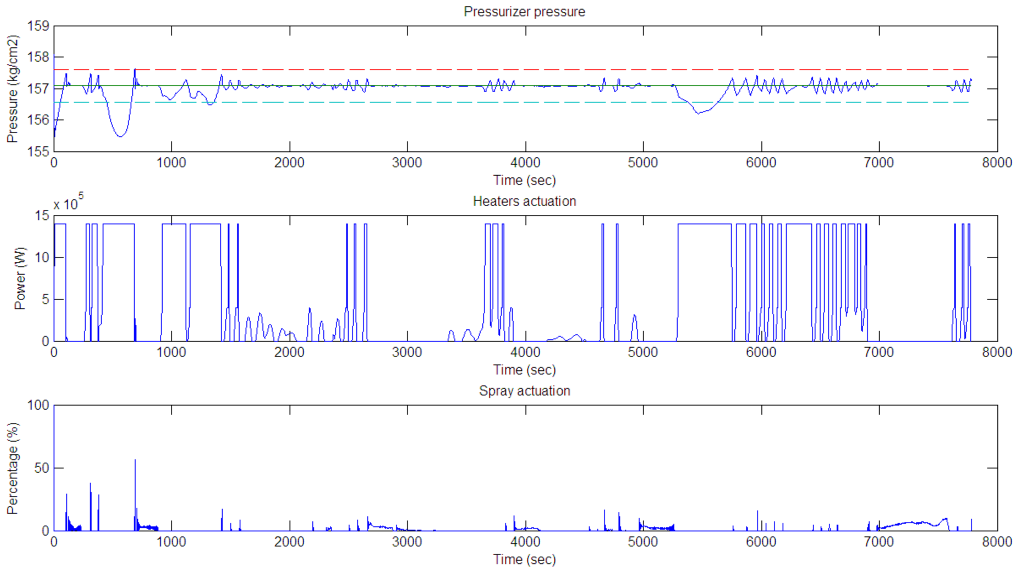


Figure 14: Fuzzy PI controller response.

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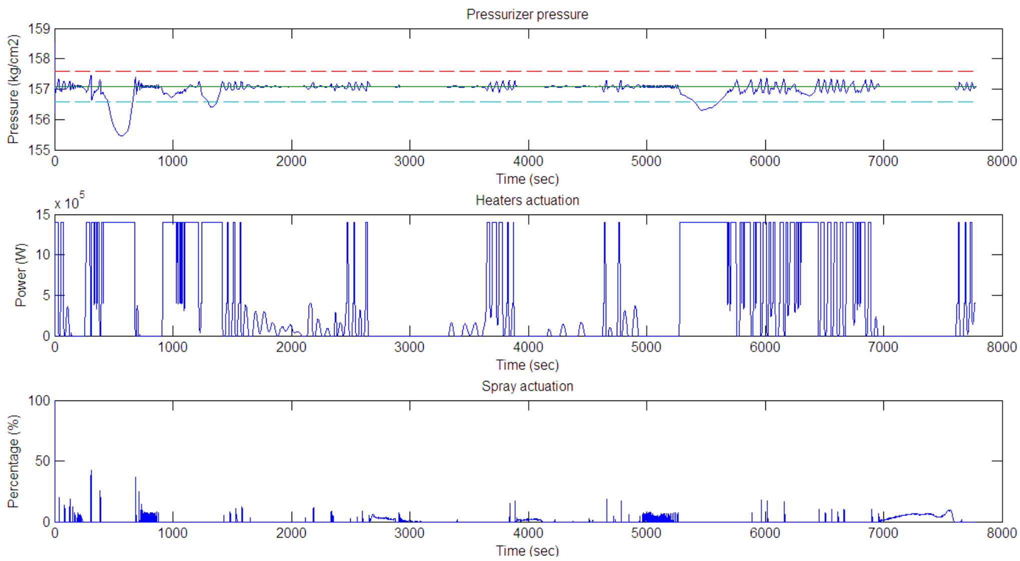

Figure 15: Conventional PID controller response.

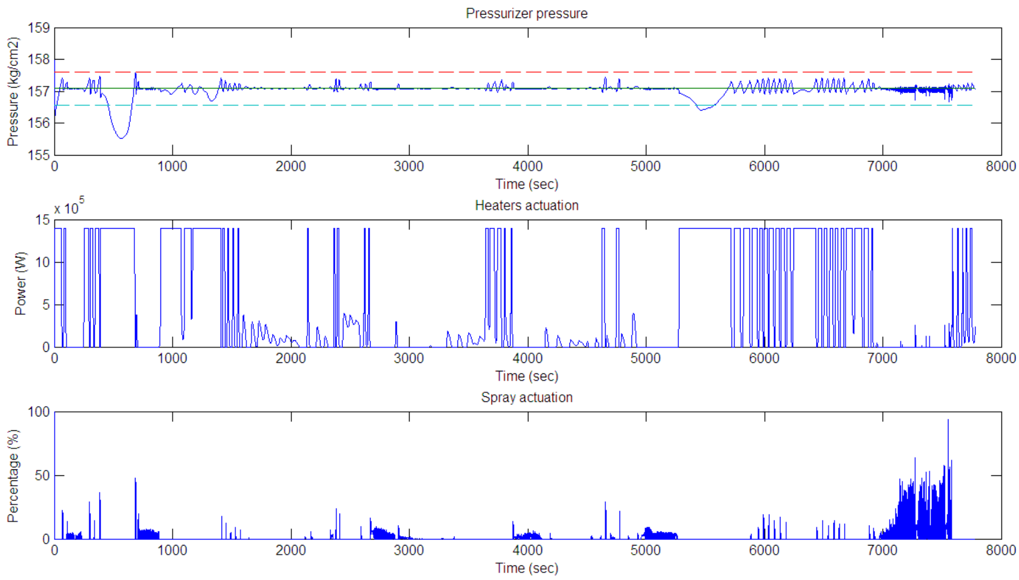

Figure 16: Fuzzy PI+PD (PID) controller response.

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