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# Level Control of Blast Furnace Gas Cleaning Tank System with Fuzzy Based Gain Regulation for Model Reference Adaptive Controller

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**Abstract:** Iron making processes and automation systems are mostly controlled by logical rules and PID controllers. The dynamic behavior of these processes varies due to factors such as raw materials, outdoor conditions, and equipment aging. Changes in system dynamics necessitate re-determination of PID controller parameters. Model reference adaptive controllers (MRACs) are used in many industrial application areas with their adaptability to variable conditions. In this study, an MRAC is applied in the gas cleaning tank system level control problem in the blast furnace facility, which is at the center of the iron making processes. In addition, fuzzy based gain regulation is proposed to improve MRAC performance. MRAC and PID controller system control results are observed and compared. The fast response and adaptation performance of the proposed fuzzy MRAC approach along with external disturbance effects are analyzed. Fuzzy based gain regulation MRAC performances show better performance especially in level change as well as disturbance effect.

**Keywords:** MRAC; PID; fuzzy MRAC; iron making processes; blast furnace gas cleaning tank system

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## 1. Introduction

Model-based inspection techniques provide system control when certain system parameters are unknown or change over time, as in iron and steel production facilities blast furnace inspection [1,2]. Model reference adaptive controller (MRAC) is an adaptive control approach, which includes a regulation mechanism and adjustable parameters when there are uncertainties or unknown changes in plant parameters [3]. In this study, it is aimed to increase the level control performance of the blast furnace gas cleaning tank system with the suggestion of regulating the MRAC adaptation speed.

The iron and steel sector has the feature of being a locomotive in the country's economy and industrialization [4,5]. It is the main input of almost every sector such as iron and steel products, durable consumer goods, construction, defense industry, automotive and shipbuilding. For this reason, the iron and steel product consumption level of a country is considered as one of the most important indicators of prosperity and development in that country [6]. The increase in the demand for iron and steel products over the years has caused countries to increase production to meet this demand by investing. The steel production process in integrated iron and steel plants begins with the reduction of iron in iron ore in facilities called blast furnace which is the end of the iron making process. As a result of reduction made by exothermic reactions, hot metal is obtained [7]. Hot metal is converted into liquid steel with the requested alloy ratios at the steelmaking plants. Then, it is cast and converted into steel in the rolling mills in accordance with customer demands [8]. These processes in steel production require energy sources such as coal, electricity and natural gas. Manufacturers are constantly trying to reduce costs by making process improvement. These activities are very important to reduce the 1.89 tons of $CO_2$ needed for 1 ton of steel [9]. The fact that iron and steel plants are businesses that operate 24/7 and produce in high quantities allows even small improvements to be made in these facilities to provide big profits on an annual basis. For example, in a facility that produces 10 million tons of pig iron annually, reducing the production cost of hot metal by $1 means that the facility earns $10 million annually from this improvement alone.

Improvements in iron making processes are made in areas such as reducing the energy raw materials used, making the endothermic reactions in the facilities efficient, eliminating the downtimes caused by unexpected failures, prolonging the useful life of the facilities and equipment by operating at the optimum level [10,11]. Almost all of these improvements are possible by controlling a variable in the process. Adjusting the ratio of iron ore and coke in the blast furnace process according to the instantaneous data of the furnace reduces the coke consumption. Combustion control in the blast furnace reduces the amount of coke gas consumed in the stove. Controlling the level of an isolation tank ensures isolation and system continuity as in the gas cleaning tank level control. The narrow amplitude and high frequency of the opening at which a control valve operates increases the service life of the valve.

Today, iron and steel plants are controlled by automation systems [12]. Processes and variables are controlled with the help of logical rules and PID controllers in automation systems software [13]. Raw materials that change over time, aging and dynamically changing systems, changing environmental conditions reduce the performance of logic rules in software and PID controllers [14,15]. In this case, the continuity of the control is ensured by changing the logical rules and controller parameters according to the process needs [15,16]. The mathematical models of the processes in the iron making processes are not known with certainty [17,18]. It is very difficult to determine the parameters of the PID controllers used in these systems by mathematical methods or methods such as root locus [19]. Experts try to determine the PID parameters either by performing tests on the system using methods such as Ziegler-Nichols with fine tuning or by making experiments based on their past experience [20,21]. Sometimes the process does not allow the procedure, trial and error methods that should be applied in methods such as Ziegler-Nichols and it is necessary to wait for the controller setting to be made. The system is forced to work with inappropriate controller parameters.

MRAC is a control method used in situations where the system parameters cannot be precisely known and the unknown parameters vary [22]. There are various adaptive control methods based on the model [23,24]. These methods require parametric models that can reasonably express system dynamics. It is very difficult to construct mathematical models of real-world problems due to the uncertainties in their structures [2]. This situation has led to research on control methods that do not need a system model. In the early 1950s, the autopilot system design problem of high-performance aircraft compelled researchers to work in the field of adaptive control. In 1958, H.P. in his study, Whitaker applied MRACs to the autopilot system of the NASA X-15 research aircraft [25]. The X-15 research aircraft performed 199 missions over 10 years [26]. Over the years, MRAC has started to be used in solving real-world adaptive control problems such as aerospace, robot arms, and industrial process control [27–30].

In this study, the applications of MRACs in iron making processes will be examined. It will be examined how MRAC can adapt to new conditions and how it can bring advantages compared to classical PID controllers in control problems in iron making processes. The gas cleaning tank system used in the blast furnace process, which has an important place in the iron making processes. The main contributions of this paper are as follows: (1) Lyapunov and MIT based MRACs are introduced to control the level of the gas cleaning tank system of the blast furnace compared to PID, (2) fuzzy based adaptation gain regulation is proposed to improve MRAC performance, (3) setpoint changes and disturbance effects are investigated using different controllers to achieve performances by means of reducing control signal amplitude.

The paper is organized in the following way: gas cleaning tank system is given in Section 2 with the level control. Section 3 includes MRAC and the proposed fuzzy MRAC approach with gain regulation, along with performance benchmarking. Finally, the results section summarizes the results obtained.

## 2. Blast Furnace Gas Cleaning Tank Level Control System

Blast furnaces are vertically located reactors that produce hot metal from iron ore, operating closed to the atmosphere. The blast furnace is filled with iron ore, coke and limestone from the upper part of the furnace, which allow the reducing reactions inside the furnace to take place. In the lower part of the furnace, there are nozzles called tuyeres above the chamber where the hot metal and slag are collected as shown in Figure 1. Hot air at a temperature of approximately 1200 °C is applied into the oven from the *t*-places. The hot air, which leaves its heat to the materials in the furnace, turns into blast furnace gas consisting of CO, $CO_2$, $N_2$, $O_2$, $H_2$ gases due to the reactions inside. Blast furnace gas is used as a fuel in electricity production due to its pressure and in iron making facilities due to the gases it contains.

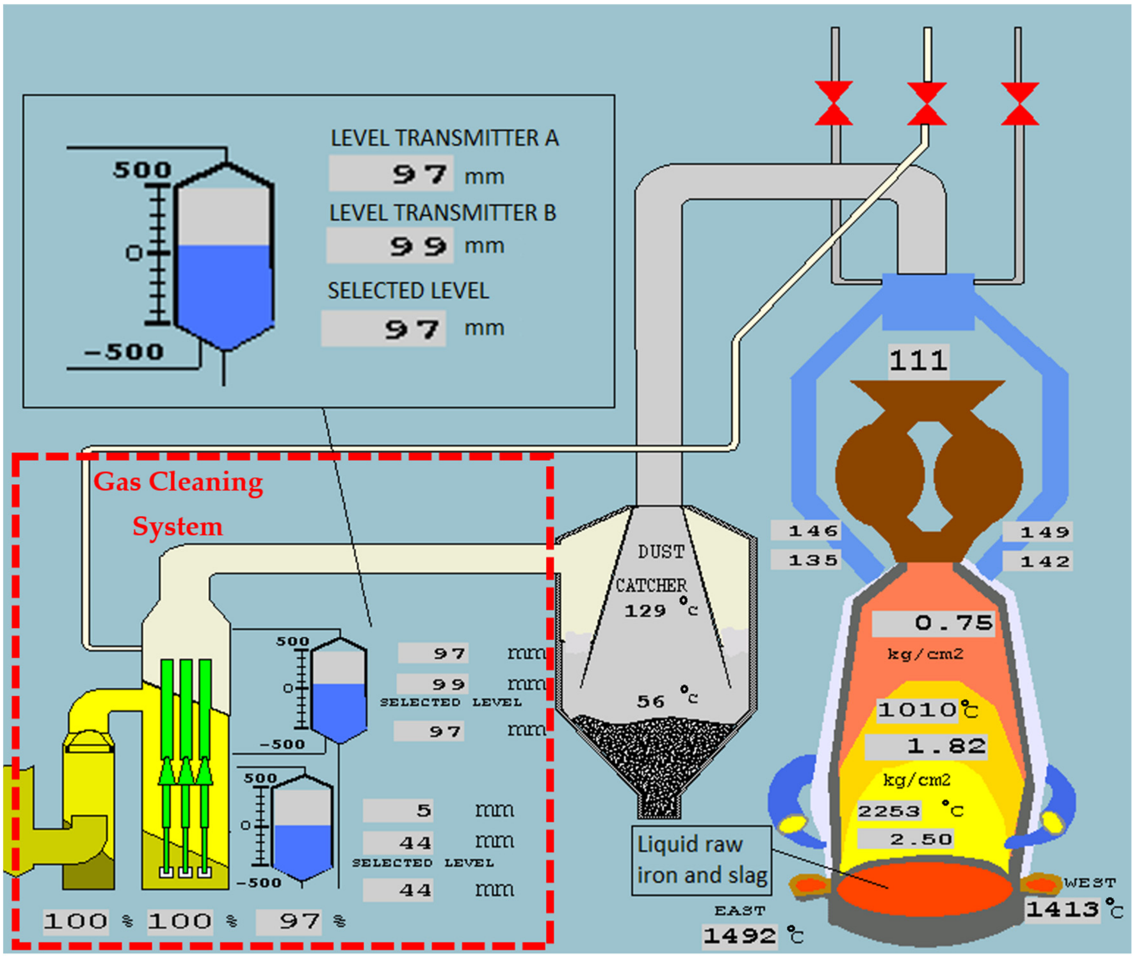


**Figure 1.** Blast furnace and gas cleaning system.

As the blast furnace gas passes through the furnace, it absorbs a large amount of dust. The blast furnace gas needs to be cleaned before it enters the turbine for electricity generation and the burners of the blast furnace stove and coke battery furnaces for use as fuel. For this purpose, the gas collected from the top of the blast furnace with the help of pipes enters a dust catcher structure that works with the cyclone logic. The gas that leaves the relatively heavy particles in the dust collector enters the blast furnace gas pressure control system. This system both fixes the blast furnace gas pressure to the value required by the furnace process and washes the gas with water. The blast furnace gas, which is dried at the outlet of this system, which is called a scrubber, becomes ready to be used in the turbine and the burner.

On the inlet side of the scrubber, where the blast furnace gas pressure is high, water is sprayed onto the gas with water sprays. Spray water also provides the separation of fine particles from the gas. Since the furnace process and the blast furnace gas line are closed to the atmosphere, there is a pressurized tank system for the discharge of the waste spray waters that take the dust in the gas. Waste water enters from the inlet of the tank and fills the tank, and the discharge valve, which is open to the atmosphere, empties the tank. During the operation of the blast furnace, it is undesirable to empty or overflow the scrubber tank. If the tank is completely empty, the blast furnace gas is released into the atmosphere and its pressure drops. When the pressure drops in the blast furnace gas cleaning line, which must operate in a closed cycle, the peak pressure of the blast furnace also decreases, the raw material layers in the furnace are mixed with each other due to the low-pressure environment formed in the furnace and the furnace regime is disrupted. In addition, the emission of blast furnace gas, which is a suffocating, flammable and polluted gas, into the atmosphere creates risks in terms of occupational health and the environment. In case the gas cleaning tank overflows, the water fills directly into the blast furnace gas pipe and there is a possibility of physical damage to the pipeline due to the weight it causes. As the overflowing water fills the water locks in the gas line, an obstacle occurs in front of the blast furnace gas and the line pressure increases. The blast furnace peak pressure, which increases with the increase in line pressure, is suddenly thrown into the atmosphere with the opening of the safety valves located at the top of the furnace. This sudden movement causes the raw material layers in the furnace to mix with each other and the furnace regime to deteriorate.

Automation systems are carried out in the control of the washer tank level. In the solution of this problem, a feedback controller is generally used, which measures the tank level information and compares it with the reference. There are two level transmitters installed on the water tank. Both level information is transmitted to the distributed control system (DCS) and via a selection algorithm in the DCS application software, one of the measurement or medium of two measurements are used as the feedback signal of the level control signal. Level transmitter A and level transmitter B, shown in Figure 1, are radar type level measurement elements. The calibration range of the both transmitters is from −500 mm to +500 mm. In Figure 1, water tank and the level measurements are zoomed in. Level value of the transmitter A is 97 mm, level value of the Transmitter B is 99 mm. It is decided to use feedback as 97 mm by DCS. The difference between the tank level signal $y_p$ measured with the aid of a sensor selected in accordance with the process and the reference signal $r$, which is the desired value of the tank level, creates the error signal e. By applying the error signal to the controller in the automation system, the controller generates the control signal $u$. The control signal is sent to the valve located at the tank outlet. It changes the amount of water discharged from the tank, by moving in the direction of opening or closing according to the state of the valve control signal.

The amount of water entering the gas cleaning tank changes continuously due to factors such as the variable blast furnace gas pressure, the irregularity in the flow of the spray water, and the muddy state of the water accumulating in the gas cleaning system. The constant variation of the amount of water entering the tank makes tank level control difficult. In addition to these sudden change effects, factors such as the aging of the valve used in the system, the accumulation of sludge at the valve inlets and outlets, and the narrowing of the pipelines due to sediments make tank level control difficult.

PID controllers are generally used to solve the tank level control problem. Under ideal conditions, local PID controllers can easily control a system expressed as in Figure 2. However, in a gas cleaning tank control system where conditions are not ideal, a valve controlled by a PID controller will have problems controlling the tank level. The PID controller, whose parameters are set according to the conditions at the time it was designed, cannot respond to sudden fluctuations in the tank system and other changes that occur over time. In such a system, the PID controller must be recalibrated at frequent intervals.

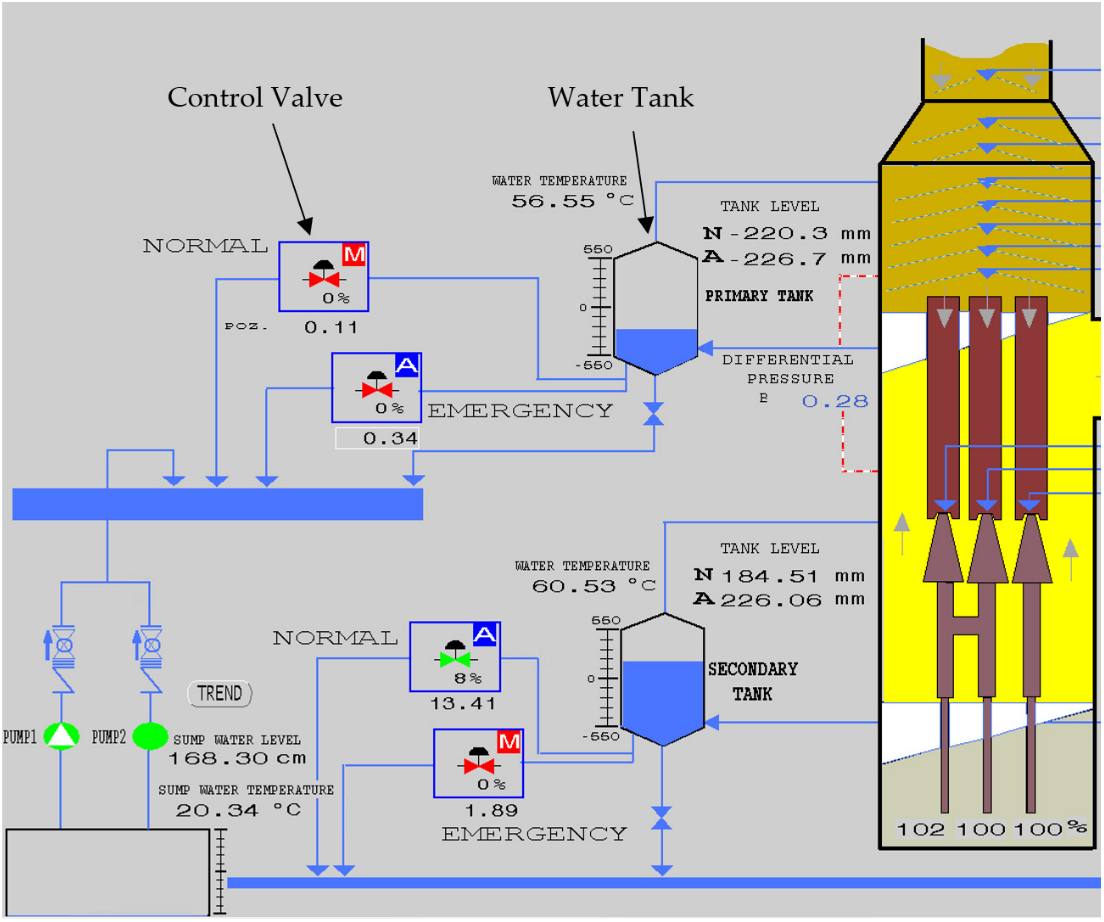


**Figure 2.** Blast furnace gas cleaning tank system and level control.

There are two important constraints in the tank level control problem. The tank should not be completely empty and should not overflow. Except for these two constraints, the tank level can be any value. The safest tank level under operating conditions is the midpoint of the tank, which is equidistant from the two constraints. For this reason, the reference input mark $r$ is selected as the midpoint of the tank for tank level control in the automation system.

There are some solutions to the tank level control problem that will positively affect the success of the controller. For example, the tank size can be designed to be very high. In this way, the tank level will be far enough from the limits even when the control system has difficulty in bringing the $y_p$ tank level closer to the reference input signal r. Alternatively, draining the water from the tank with two independent tanks increases the success of the controller. Although using a large tank or two tanks may seem to be a solution, it causes additional costs and causes inefficient use of the area where the blast furnace facility is installed. There are two valves at the outlet of the gas cleaning tank shown in Figure 2. These valves can be used in two different ways. One of the valves is constantly held at a certain opening. The second valve opening is also controlled by PID. In this case, the valve, which has a fixed opening value, takes the water discharge on itself at a certain rate. The valve controlled by the PID controller also provides precise control of the tank level, trying to compensate for sudden changes in level. Another approach is to control both valves by different PID controllers. In this approach, one of the PID controllers is set to slow and the other to fast character. Under normal conditions, tank level control is done by a slow response time PID controller. In this case, the valve controlled by the fast response PID controller is in the closed position. When the tank level approaches the maximum set value, the fast response time PID controller is activated and helps to stabilize the level by increasing the water discharge rate.

Figure 3 shows the data of blast furnace scrubber tank level control working with a PID controller. In the controlled system, there are two valves to discharge water from the tank. Both of these valves are controlled by a PID controller. In the control of the valve, which is expressed as a normal valve, the reference value of the tank level is selected as half of the tank height. The reference value determined for the valve called the emergency valve was determined as 20% more than that of the normal valve. Accordingly, the tank level is controlled only by the normal valve under normal conditions. In cases where the normal valve is not sufficient, the emergency valve is also activated and helps level control.

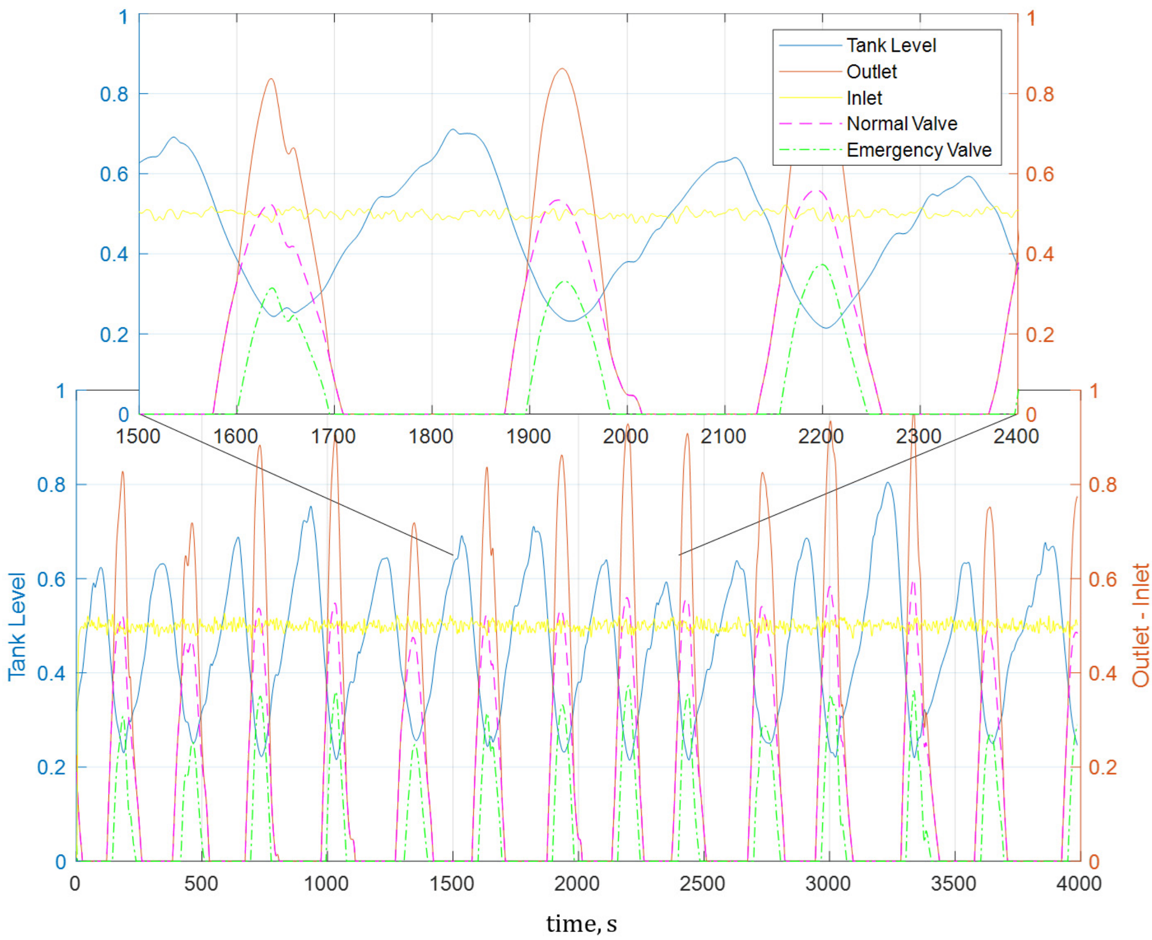


**Figure 3.** Gas cleaning tank system level change with changes of inlet and outlet valve.

The data in Figure 3 shows the variation of the water level with the total operation of the normal valve and the emergency valve. Here, the 4000 s change in the tank level is constantly oscillating and the emergency valve is needed in every oscillation. The details of this change between 1500–2400 s include the support given by the total of the emergency valve and the normal valve. Firstly, the normal valve controls the tank level. When the tank level still continues to increase, the emergency valve opening has also increased and the rate of level discharge from the tank has increased. After the tank level reached its maximum value, it started to decrease again. With the decrease in the tank level, first the emergency valve and then the normal valve were closed and level control continued. The cycle is approximately 300 s. It should be noted that the inlet valve will fill the tank in approximately 60 s.

Different solution approaches can also be used for the gas cleaning tank level control problem. However, when it is desired to go to the solution with classical PID controllers, traditional solutions are not successful enough. These approaches, which are realized with the use of excessive and inefficient resources, also cause extra costs. Different approaches have been used in the literature for the control of systems where sudden and long-term changes occur, such as the gas cleaning tank level control problem [31]. Thanks to technological developments and increasing processing speeds, iterative operations, and the use of fuzzy logic controllers, transfer functions and mathematical model operations can be performed with automation systems. PID controllers whose parameters are constantly updated can be used for systems that need a different PID controller due to the change in system characteristics [32]. The control performance can be increased by manipulating the PID controller output signal u with a fuzzy logic controller, which reduces the control performance due to external disturbances and the time-dependent change of the system dynamic response [33].

The mathematical model of a system whose system characteristics are constantly changing can be created continuously with the data collected from the process and system identification methods, and this model can be controlled by model predictive controllers [23]. MRACs, which are the subject of this study, can also be used where the classical PID controller is insufficient [30].

## 3. Fuzzy Model Reference Adaptive Controller

In this section, the proposed fuzzy MRAC approach will be discussed along with the MRAC structures applied to scrubbing tank system inspection.

### 3.1. Model Reference Adaptive Controller

MRACs do not need a mathematical model of the system like classical control methods [34,35]. In the most general sense, MRAC consists of reference model, adaptation algorithm and controller. Figure 4 shows the MRAC structure designed to control a system whose mathematical model is unknown. MRAC is a control method that tries to bring the error between two output signals closer to zero by approximating the output of the system (real system) to be controlled and the reference model output [36].

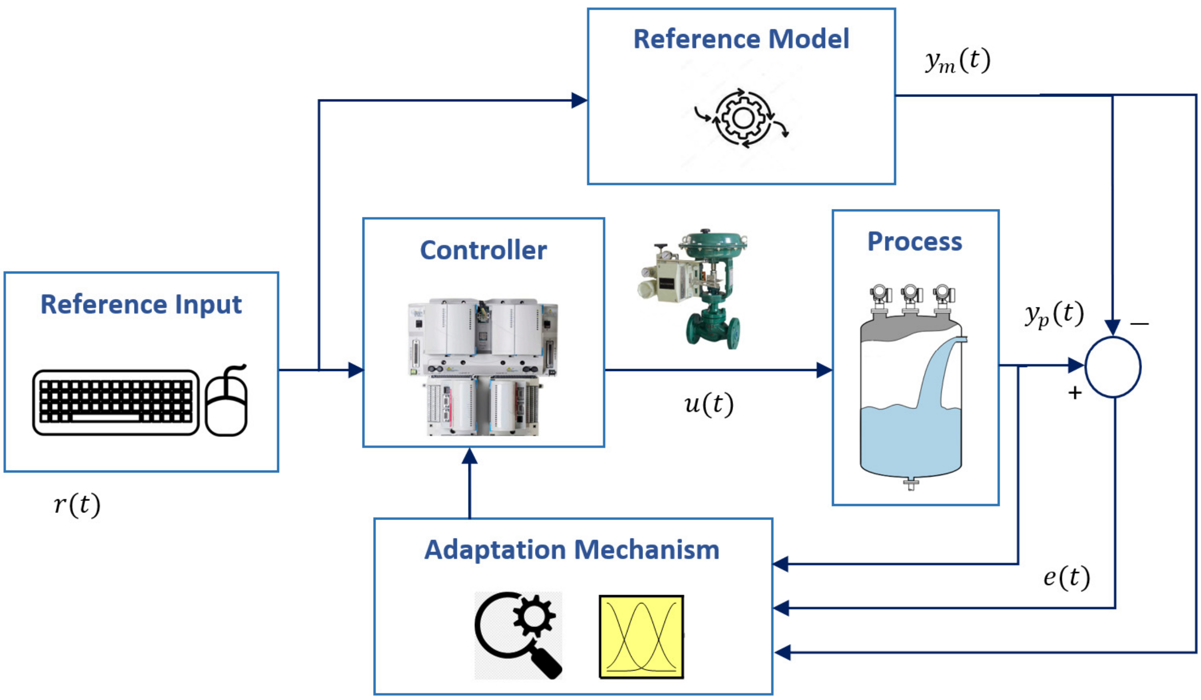


**Figure 4.** MRAC block structure applied to gas cleaning tank level control process.

In general, MRAC consists of reference input signal, controller, system, reference model and adaptation algorithm components. Here, the system shows the mathematical model of the system that is the subject of the control problem. In MRAC applications, the mathematical expression of the system is often unknown. The controller block specifies the control method specified by the designer. The reference model is a mathematical model determined by the designer. The adaptation mechanism and the controller, which are the last components of MRAC, as seen in Figure 4, is a mathematical method that tries to make the error signal zero.

Before creating the reference model, the designer examines the physical conditions of the real system and then determines what the expected response of the system response should be. According to the desired response, the reference model parameters are determined. When the reference input is applied to the reference model, $y_m$ reference model output signal occurs. The same reference input is applied to the controller and the controller generates a control signal. After being affected by the control signal, real system generates $y_p$ process output signal. The main effort of MRAC is to minimize the error signal $e$, between $y_p$ and $y_m$

$$e(t) = y_p(t) - y_m(t), \tag{1}$$

is defined as the difference between the system whose parameters are $a$ and $b$ output $y_p$ and the reference model output $y_m$. $y_p$ and $y_m$ signals are generated by the plant mathematical expression whose parameters are $a$ and $b$ and the reference model whose parameters are $a_m$ and $b_m$ defined as,

$$\frac{dy_p}{dt} = -ay_p(t) + bu(t) \ and \ \frac{dy_m}{dt} = -a_m y_m(t) + b_m r(t) \tag{2}$$

where $r$ is reference input and $u$ is the control signal. To obtain the control signal $u$, in Equation (3), there is a control law. Control law is a mathematical method that includes single or multiple $\theta$ parameters. Reference input is applied to the control method and due to the control law and values of the $\theta$ parameters, control signal $u$ is generated. Selected control law in this study is defined as

$$u(t) = \theta_1 r(t) - \theta_2 y_p(t), \tag{3}$$

When the control signal $u$ is applied to the system $y_p$, output signal is obtained as,

$$\frac{dy_p}{dt} = -ay_p(t) + b\big(\theta_1 r(t) - \theta_2 y_p(t)\big) \tag{4}$$

$$\frac{dy_p}{dt} = -(a + b\theta_2)y_p(t) + b\theta_1 r(t) \tag{5}$$

In Equation (5), to minimize the error, ideal values for $\theta$ paramerters are,

$$\theta_1 = \frac{b_m}{b} \ and \ \theta_2 = \frac{a_m - a}{b} \tag{6}$$

To reduce the error signal between $y_p$ and $y_m$, a cost function is created. When MIT rule is used to develop an adaptation mechanism, the cost function is defined as,

$$J(\theta) = \frac{e(\theta)^2}{2} \tag{7}$$

In Equation (5), it is seen that $y_p$ depends on the values of $\theta$ parameters. Thus, adjusting $\theta$ parameters in one direction, reduces $e(\theta)$ value, where $\theta$ is the adjustable parameter. According to the MIT rule, it is reasonable to change the parameter in the direction of the negative gradient of $J$,

$$\frac{\mathrm{d}\theta}{\mathrm{dt}} = -\gamma \frac{\partial J}{\partial \theta} = \gamma \frac{\partial e}{\partial \theta} \tag{8}$$

where $\gamma$ deretmines the adaptation rate. Adaptation speed is proportional to the value of $\gamma$. In the Equation (5), $y_p$ can be expressed as

$$y_p(t) = \frac{b\theta_1}{p + a + b\theta_2} r(t) \quad and \quad p = \frac{dx(t)}{dt} \tag{9}$$

Then, the error signal between can be $y_p$ and $y_m$ as follows,

$$e(t) = \frac{b\theta_1}{p + a + b\theta_2} r(t) - y_m \tag{10}$$

Then, partial derivatives shown in Equation (8) can be calculated;

$$\frac{\partial e}{\partial \theta_1} = \frac{b}{p + a + b\theta_2} r(t) \tag{11}$$

$$\frac{\partial e}{\partial \theta_2} = -\frac{b^2\theta_1}{(p + a + b\theta_2)^2} r(t) = -\frac{b}{p + a + b\theta_2} y(t) \tag{12}$$

When the ideal value of $\theta_2$ is used, partial derivative of error and adaptation methods of $\theta$ parameters are shown as,

$$\frac{\partial e}{\partial \theta_1} = \frac{b}{p + a_m} r(t) \tag{13}$$

$$\frac{\partial e}{\partial \theta_2} = \frac{b}{p + a_m} y(t) \tag{14}$$

$$\frac{d\theta_1}{dt} = -\gamma' b \frac{1}{p + a_m} r(t) \tag{15}$$

$$\frac{d\theta_2}{dt} = -\gamma' b \frac{1}{p + a_m} y(t) \tag{16}$$

If adaptation rate $\gamma$ is considered

$$\gamma = \gamma' \left( \frac{b}{a_m} \right) \tag{17}$$

Then adaptation method of parameters are shown in Equations (18) and (19),

$$\frac{d\theta_1}{dt} = -\gamma \left( \frac{a_m}{p + a_m} r(t) \right) e(t) \tag{18}$$

$$\frac{d\theta_2}{dt} = \gamma \left( \frac{a_m}{p + a_m} y(t) \right) e(t) \tag{19}$$

In this approach, known as the MIT rule, the limits of the $\gamma$ value, which determines the adaptation rate for MRAC, are system dependent and it is not possible to specify exact limits. If the adaptation speed is increased or decreased too much, the $\theta$ parameter values oscillate too much and instability occurs [36]. Due to the uncertainties in the MIT rule, in order to construct the MRAC adaptation algorithm, a positive definite and negative definite

Lyapunov function is needed in the approach based on the Lyapunov stability concept [37]. Similar to the MIT method, derivative of error signal over time is expressed,

$$\frac{de}{dt} = \frac{dy_p}{dt} - \frac{dy_m}{dt} \tag{20}$$

$$\frac{de}{dt} = -ay_p(t) + b\big(\theta_1 r(t) - \theta_2 y_p(t)\big) - a_m y_m(t) + b_m r(t) \tag{21}$$

After adding and removing $a_m y_p(t)$, expression in Equation (21) becomes,

$$\frac{de}{dt} = -a_m e(t) - (b\theta_2 + a - a_m)y_p(t) + (b\theta_1 - b_m)r(t) \tag{22}$$

By using Equation (22), candidate for Lyapunov function is obtained as follows,

$$V(e, \theta_1, \theta_2) = \frac{1}{2}\left(e^2 + \frac{1}{b\gamma}(b\theta_2 + a - a_m)^2 + \frac{1}{b\gamma}(b\theta_1 - b_m)^2\right) \tag{23}$$

After taking derivative of Lyapunov function,

$$\frac{dV}{dt} = e\frac{de}{dt} + \frac{1}{\gamma}(b\theta_2 + a - a_m)\frac{d\theta_2}{dt} + \frac{1}{\gamma}(b\theta_1 - b_m)\frac{d\theta_1}{dt} \tag{24}$$

$$\frac{dV}{dt} = -a_m e^2 + \frac{1}{\gamma}(b\theta_2 + a - a_m)\left(\frac{d\theta_2}{dt} - \gamma ye\right) + \frac{1}{\gamma}(b\theta_1 - b_m)\left(\frac{d\theta_1}{dt} + \gamma re\right) \tag{25}$$

Although it is noted that there is no systematic way to find a suitable Lyapunov function, the adaptation rule in this approach [38]

$$\frac{d\theta_1}{dt} = -\gamma r(t)e(t) \quad and \quad \frac{d\theta_2}{dt} = \gamma y_p(t)e(t) \tag{26}$$

is obtained. It should be noted that this rule is similar to the MIT rule in (6). The only difference is that there is no need for additional filtering in the reference model dynamics. Accordingly, the Lyapunov-based MRAC block structure is given in Figures 4 and 5. In Figure 5, $G_m(s)$ and $G(s)$ are representing the mathematical model of reference model and process. In both the MIT approach and the Lyapunov approach, the speed of adaptation is directly related to the choice of $\gamma$. In this study, fuzzy logic-based error and error variation-based gain regulation approach is proposed to determine the adaptation rate.

### 3.2. Fuzzy MRAC with Automatic Gain Regulation

Fuzzy logic control is a knowledge-based control system and is basically based on decision-making based on rule base. Here, it is aimed to decide the MRAC adaptation speed according to the error and error change. The fuzzy logic rules change the value of $\gamma$ according to the size of the error. Triangle/Gaussian function has been selected as membership function using the Mamdani fuzzy inference as well as using the centroid defuzzification.

In fuzzy rule-based mapping, there are five states {Very Small (VS), Small (S), Big (B), Very Big (VB), Extreme Big (EB)} for error, three {Negative Big (NB), Small (S), Positive Big (PB)} states for error variation, and five (VS, S, B, VB, EB) for the adaptation rate coefficient. The rules, which are determined as 15 in total, define the conditions where the error is low but tends to decrease, the error is at an acceptable level and decreasing, or the error is high and gradually increasing. In this way, it will be possible to adapt the $\gamma$ value. In Table 1, the rule base based on the variation of error with error is determined for the adaptation gain. Input and output membership functions of the proposed fuzzy based gain regulation are given in Figure 6.

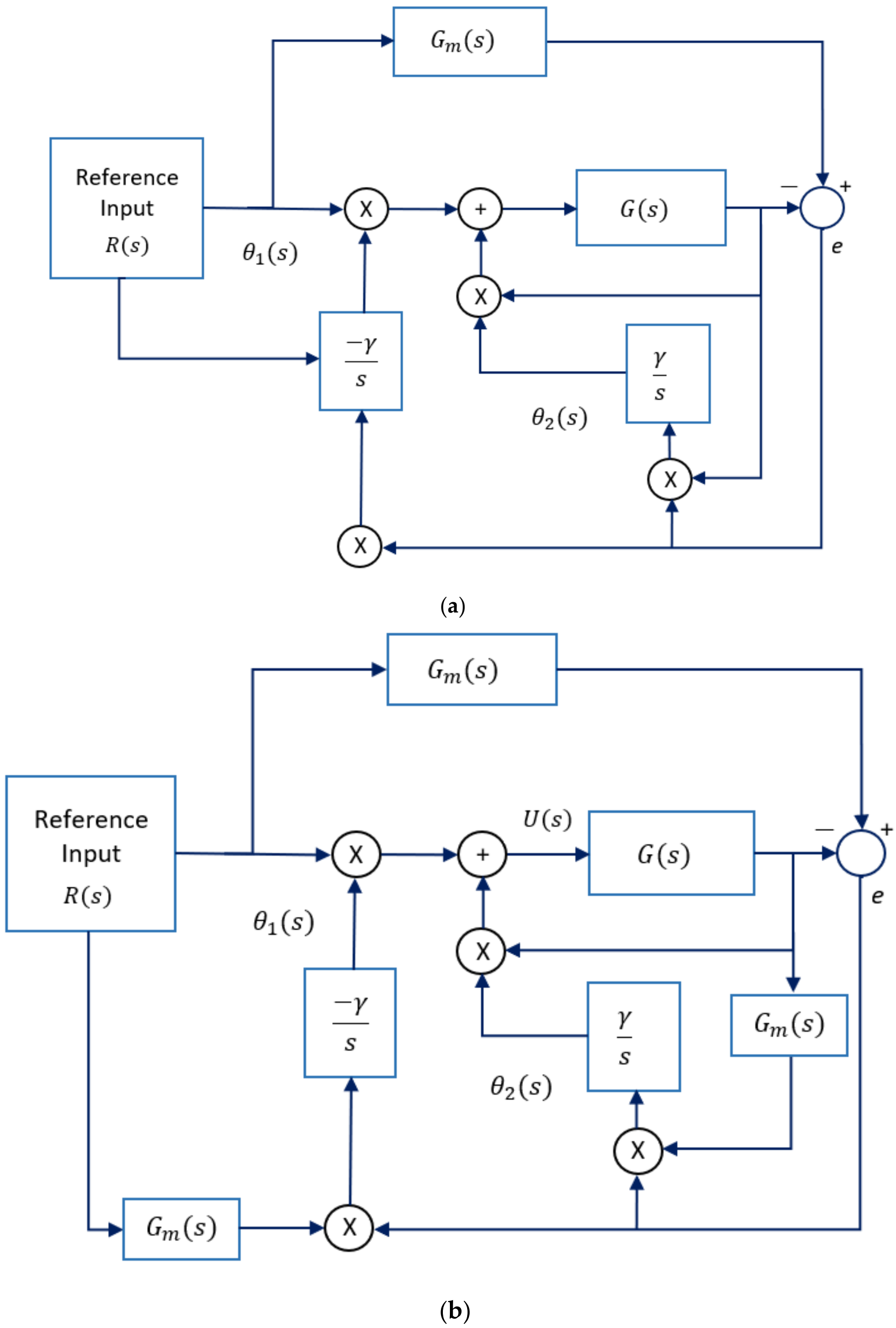


**Figure 5.** MRAC Structure: (**a**) Lyapunov; (**b**) MIT rule.

**Table 1.** Fuzzy MRAC rule base for adaptation gain.

| **\|*e*\| and *de*/*dt*** | **NB** | **S** | **PB** |
|---|---|---|---|
| VS | VS | VS | VS |
| S | S | VS | S |
| B | B | S | B |
| VB | VB | B | VB |
| EB | EB | VB | EB |

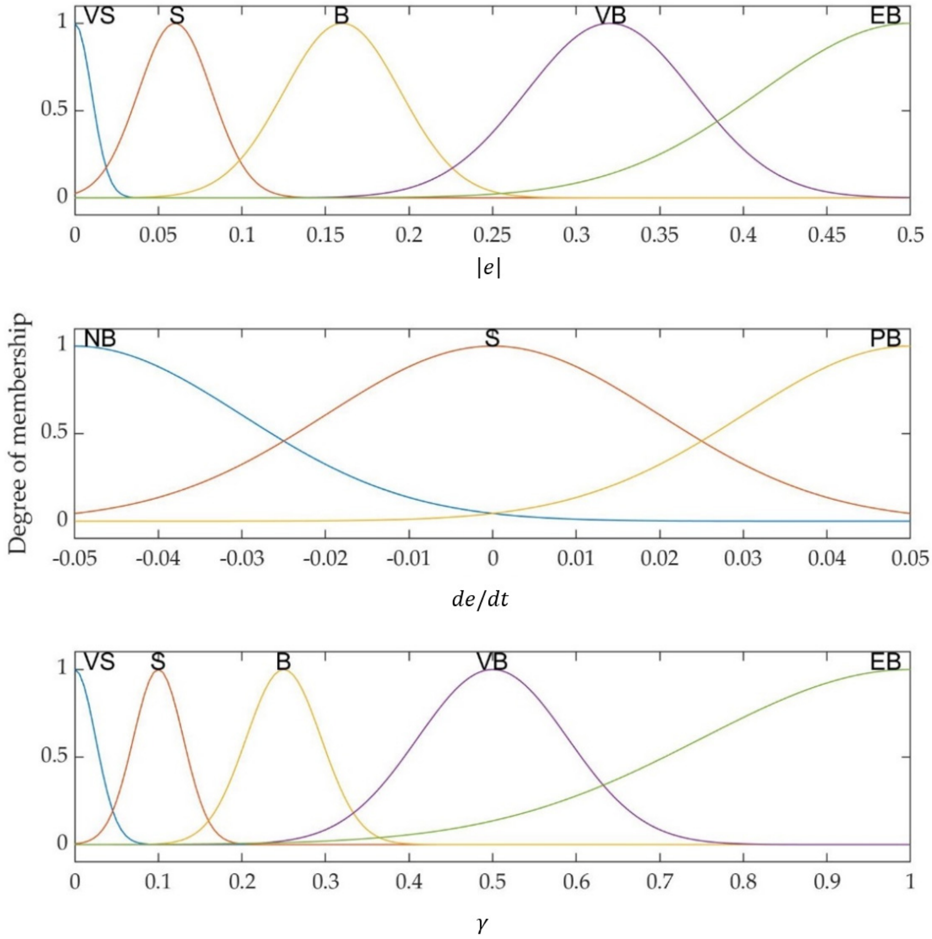


**Figure 6.** Fuzzy input/output membership functions.

The fuzzy MRAC application with gain regulation is given in Figure 7. The fuzzy-based adaptation rate regulation can be examined together with the external disturbance effect of the gas cleaning tank system.

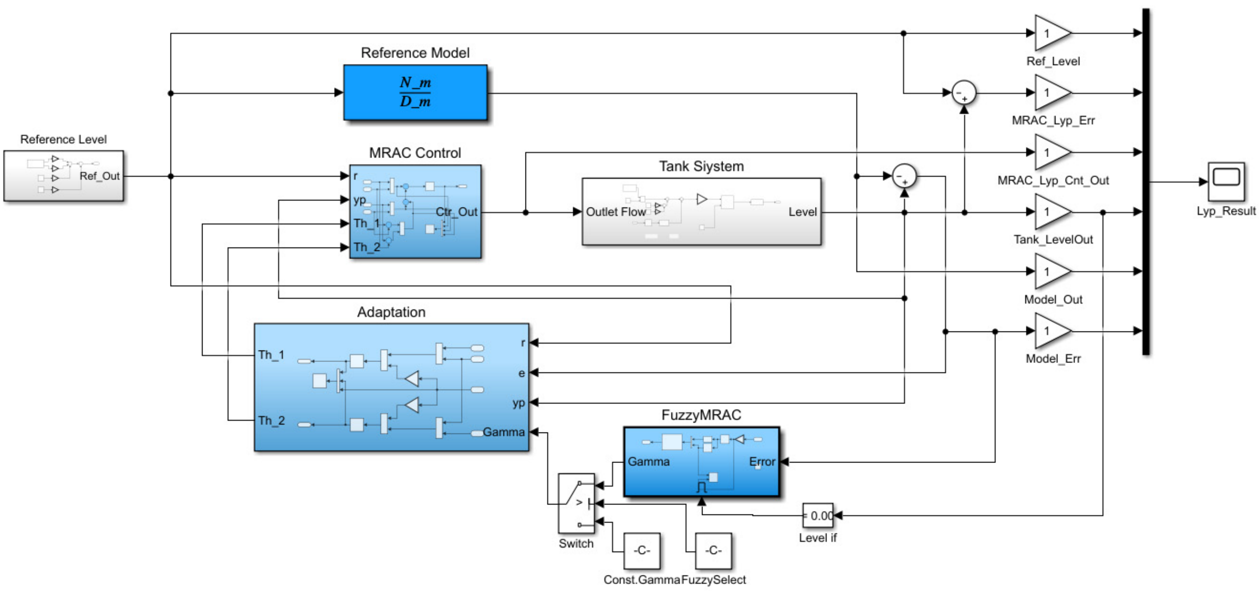


**Figure 7.** Two-input fuzzy MRAC model.

## 4. Blast Furnace Gas Cleaning Tank Level Inspection Results and Discussion with Fuzzy MRAC

In this section, a detailed performance evaluation of the proposed fuzzy MRAC approach in gas cleaning tank system level control is made. Lyapunov based MRAC is preferred because of its stability advantage in solving the tank level control problem but also MIT based MRAC has been examined. According to the data collected from the real system given in Figure 3, the control of the defined system with MRAC is examined. Here, fuzzy MRAC performance is compared with the PID controller and constant adaptation rated MRACs as response times and errors. In addition, the external disturbance effect of the system is also examined. To evaluate the performance of the controllers more accurately, not only percent overshoot and settling time but also the following performance indexes were employed for given simulation time $t_s$,

- Integral of the squared error (ISE) defined as:

$$\text{ISE} = \frac{1}{t_s}\int_0^{t_s} |r(t) - y_p(t)|^2 dt \tag{27}$$

- Integral of the control signal change (ICSC) defined for given averaged control signal $\overline{u}(t)$ as:

$$\text{ICSC} = \frac{1}{t_s}\int_0^{t_s} |u(t) - \overline{u}(t)|^2 dt \tag{28}$$

Here, in order to compare the controller performances, a 3000 s simulation study is carried out in which the step response and external disturbance are examined first. The tank water level is increased from zero to 50% in 60 s, and the step response is examined by reaching 60% between 1000–1500 s. The external disturbance effect is applied in the reverse direction of 10% between 2000–2500 s. The effect of change in the rate of adaptation in the MRAC structure is also examined, and the performances of PID and proposed fuzzy MRAC are evaluated.

Considering that the gas cleaning tank system is filled in approximately 60 s in Figure 3, the reference model for MRAC was chosen with a time constant of 12. Both MIT and Lyapunov approaches are evaluated for the adaptation rate of 0.01, 0.04, and 0.1. It is assumed that the mathematical model of the tank level control system is unknown as the real blast furnace process, thus the Ziegler Nichols approach is used to tune PID controller parameters. First, integral and differential gains are set to zero and proportional gain is raised until the system output has an undamped oscillation. Proportional gain and oscillation frequency at this stage are used to determine the PID parameters [20]. After following the steps of the Ziegler Nichols method, several tests are made on the tank water level control system to optimize the PID parameters. Note that optimal PID parameters for tank level control systems are tuned as 1.5 for P, 0.013 for I, and 1.5 for D.

Figure 8 shows the gas cleaning tank system level control step response with the external disturbance effect, together with the results of fuzzy MRAC, MRAC (adaptation rate 0.04), and PID for both MIT and Lyapunov approaches. When the details of the step response are examined in Figure 8, it is observed that the overshoot is very high despite the fast response of the PID; the response is slow with a constant adaptation speed and less overshoot and fast response in the fuzzy MRAC approach. Obtained overshoot and settling time information as well as ISE in (27) and ICSC in (28) values are given in Table 2. The Lyapunov fuzzy MRAC approach shows a fast response 140 s settling time and smaller ISE and ICSC values. ICSC values show the variation of the controlled valve in the gas cleaning tank system so that valve age performance can be evaluated. It is also seen in Figure 8 that the fuzzy MRAC approach reacts faster to the external disturbance effect than the others.

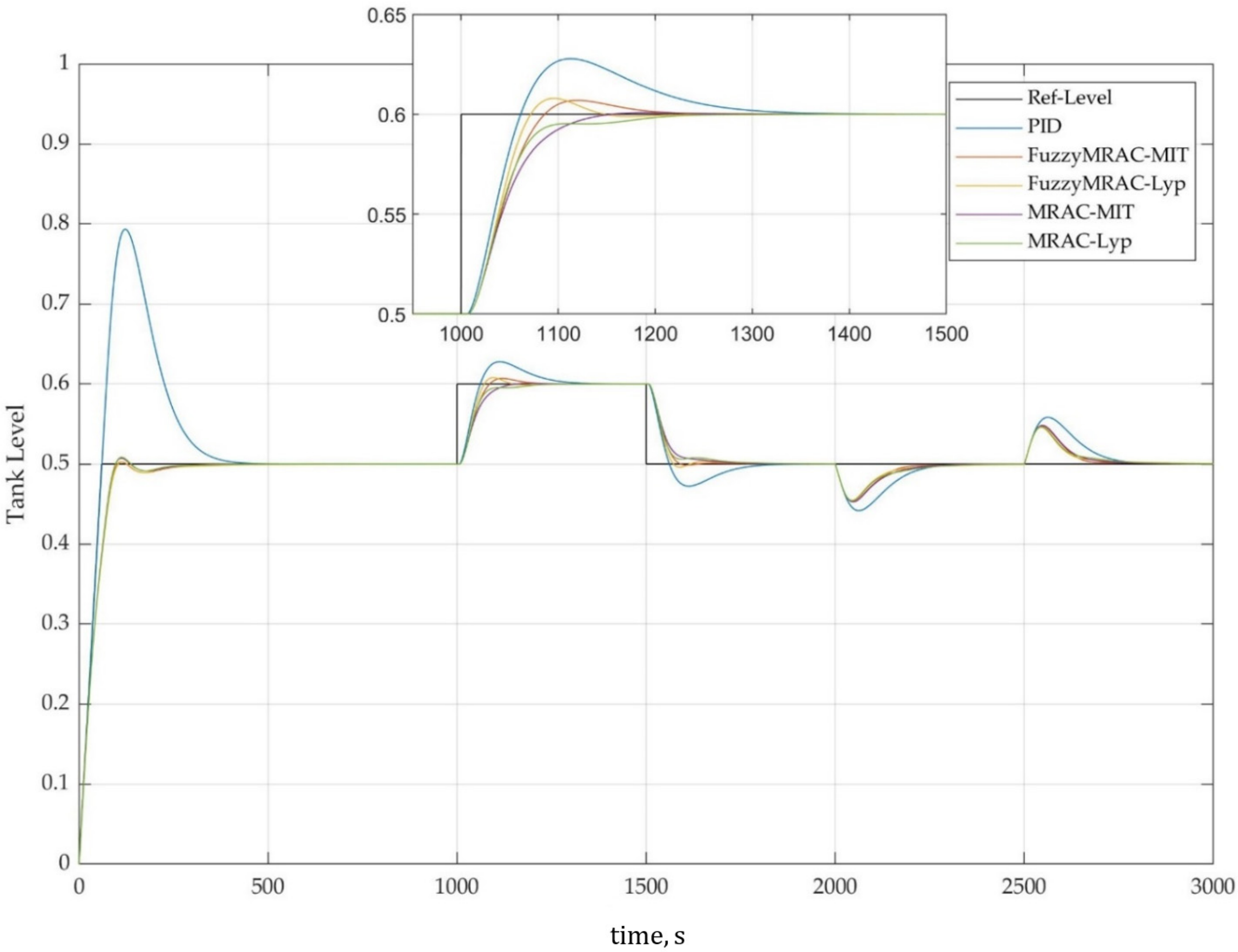


**Figure 8.** Gas cleaning tank system level control using PID, MRAC and fuzzy MRAC.

**Table 2.** MIT and Lyapunov based MRAC results compared to PID.

| Controller | Adaptation Gain | Overshoot (%) | Settling Time (s) | ISE | ICSC |
|---|---|---|---|---|---|
| PID | - | 27% | 325 | 0.003067 | 0.005607 |
| MIT MRAC | 0.01 | 0 | >500 | 0.000423 | 0.004198 |
| | 0.04 | 2% | 175 | 0.000407 | 0.004313 |
| | 0.10 | 37% | >500 | 0.000571 | 0.004586 |
| MIT fuzzy MRAC | [0.02, 0.09] | 7% | 150 | 0.000397 | 0.004343 |
| Lyapunov MRAC | 0.01 | 0 | >500 | 0.000382 | 0.004205 |
| | 0.04 | 0 | 190 | 0.000388 | 0.004339 |
| | 0.10 | 29% | 450 | 0.000555 | 0.004548 |
| Lyapunov fuzzy MRAC | [0.02, 0.09] | 8% | 140 | 0.000379 | 0.004367 |

The time-dependent changes of the $\theta_1$ and $\theta_2$ parameters of the fuzzy MRAC and MRAC (adaptation rate 0.01, 0.04 and 0.1) operating in Figure 8 can be seen in Figure 9 for MIT rule and Figure 10 for Lyapunov rule. The $\theta_1$ and $\theta_2$ parameters changed more slowly in the low-adaptation conditions ($\gamma$ is 0.01) than in the high-adaptation conditions ($\gamma$ is 0.1). The $\theta_1$ and $\theta_2$ parameters did not converge the final value in 1000–1500 s when $\gamma$ is 0.01 for both MIT and Lyapunov rule. In addition, the parameters are still oscillating when $\gamma$ is 0.1. The fuzzy MRAC approach has helped faster adaptation, especially for reference level change as well as disturbance effect, as shown in Figures 9 and 10. Fuzzy based adaptation gain regulation has been necessary to update MRAC parameters. This will show one has to consider adaptation rate change, such as fuzzy MRAC for industrial applications.

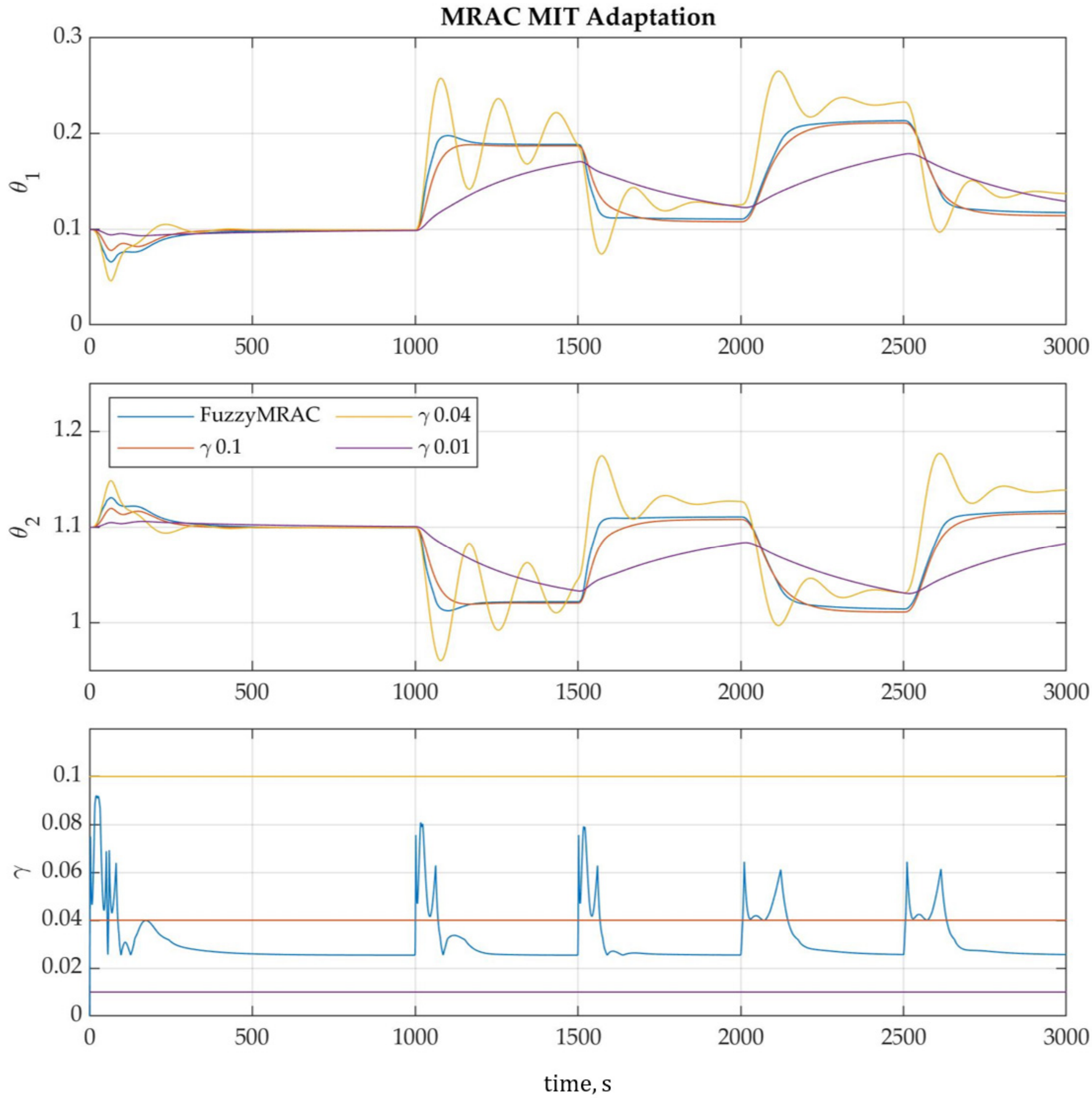


**Figure 9.** MIT rule fuzzy MRAC, MRAC (adaptation rate 0.01, 0.04 and 0.1) parameter adaptation $\theta_1$, $\theta_2$, and $\gamma$.

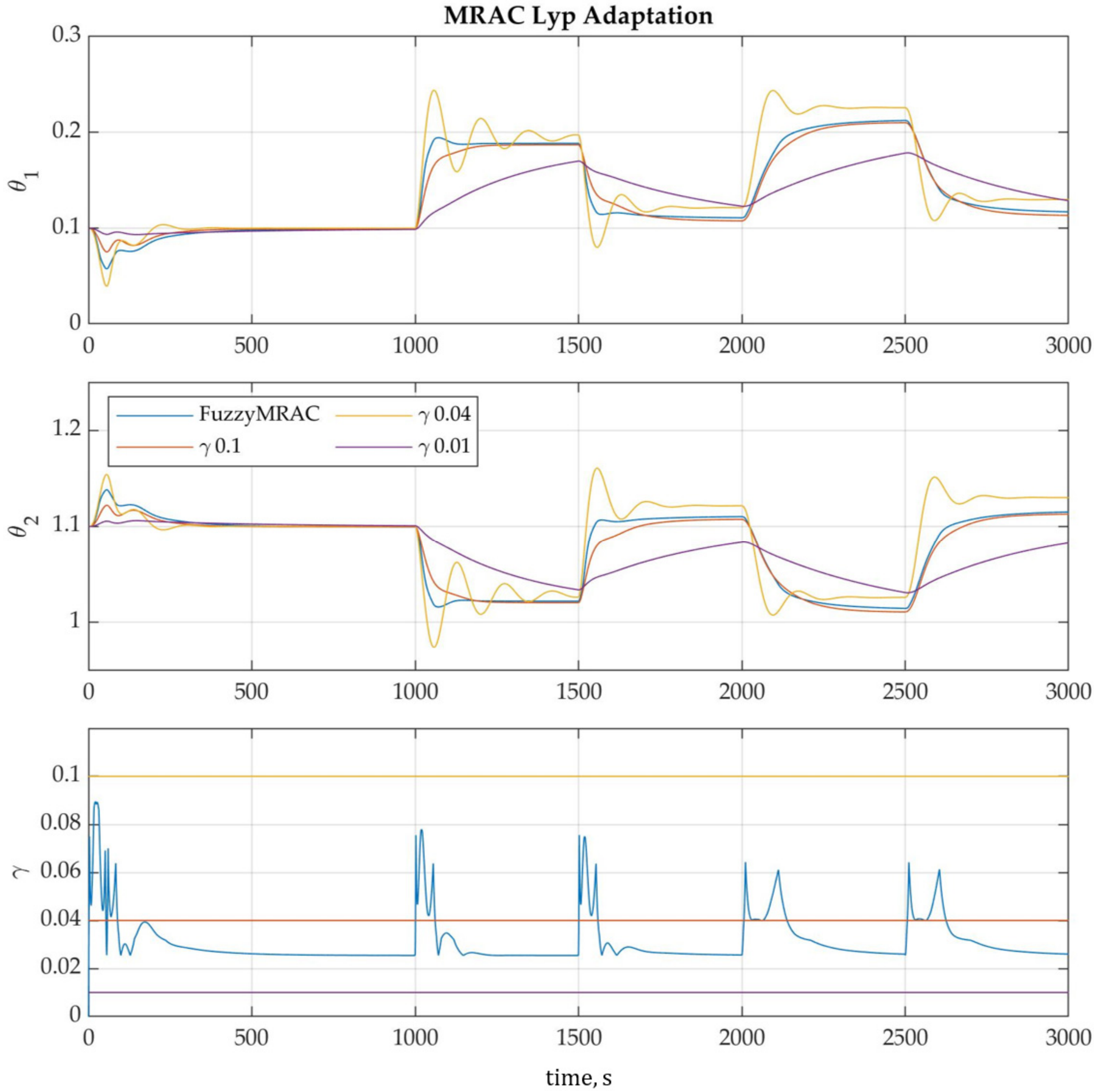


**Figure 10.** Lyapunov rule fuzzy MRAC, MRAC (adaptation rate 0.01, 0.04 and 0.1) parameter adaptation $\theta_1$, $\theta_2$, and $\gamma$.

The effect of adaptation rate on MRAC has been observed in studies. In determining the adaptation rate, the gain-regulated fuzzy MRAC performance designed by using the amplitude of the error signal in Equation (1) and the variation of the error with time, Figure 11 for MIT rule, Figure 12 for Lyapunov rule and Figure 13 for PID show the application results of the tank level control problem. Depending on the reference information, the changes in the MRAC adaptation parameters and the adaptation speed are seen together with the change of the tank water level and the control sign. In these figures, it is observed that the tank level reaches the desired value in 200 s for MRAC but in 400 s for PID. At 1000 s, the tank level oscillated with the effect of the step reference level applied to the system, and the level was fixed at 1500 s. Upon increasing the reference value of the tank level, MRAC generated the necessary control signal and provided the level control. These figures also show control signal as well as tank level error.

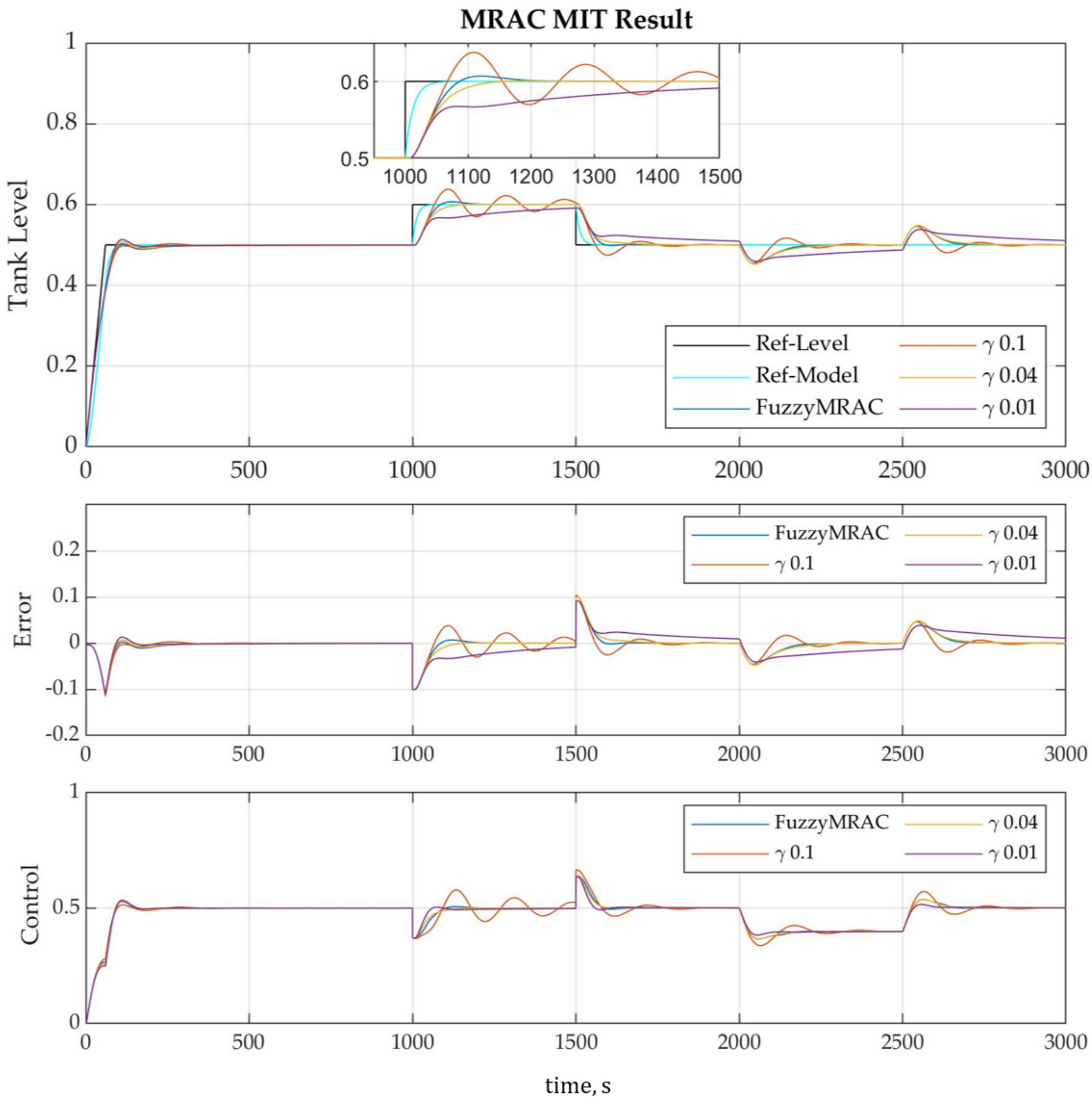


**Figure 11.** Tank level control for MIT rule fuzzy MRAC and MRAC for different adaptation rates.

It was observed that the PID controller could not prevent the oscillation at the tank level during the operation. There are big changes for control signal for PID compared to MRAC. After changing the level reference, it reached the desired value without creating oscillations. In contrast, tank level oscillation was observed in most of the PID control. The MRAC oscillated a little after the external disturbance effect, and after the adaptation of the $\theta$ parameters, it achieved control much faster than the PID.

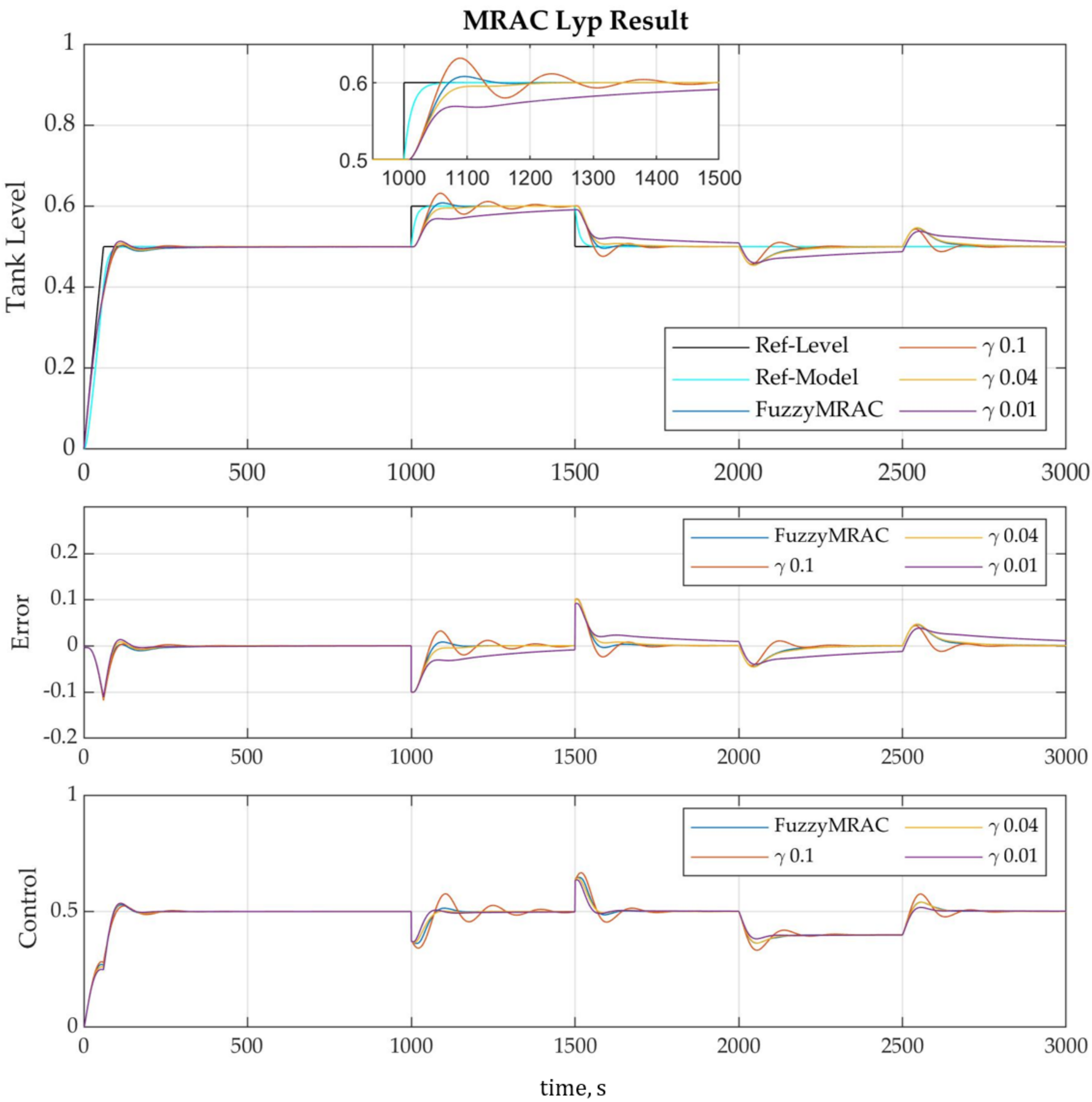


**Figure 12.** Tank level control for Lyapunov rule fuzzy MRAC and MRAC with different adaptation rates.

In order to compare the controller performances, a 3000 s simulation study is carried out in which the variable reference level is examined secondly. The tank water level is increased from zero to 50% in 60 s, and the sinusoidal reference signal has been applied to the system after 500 s. The effect of change in the rate of adaptation in the MRAC structure is also examined, and the performances of PID and proposed fuzzy MRAC are evaluated.

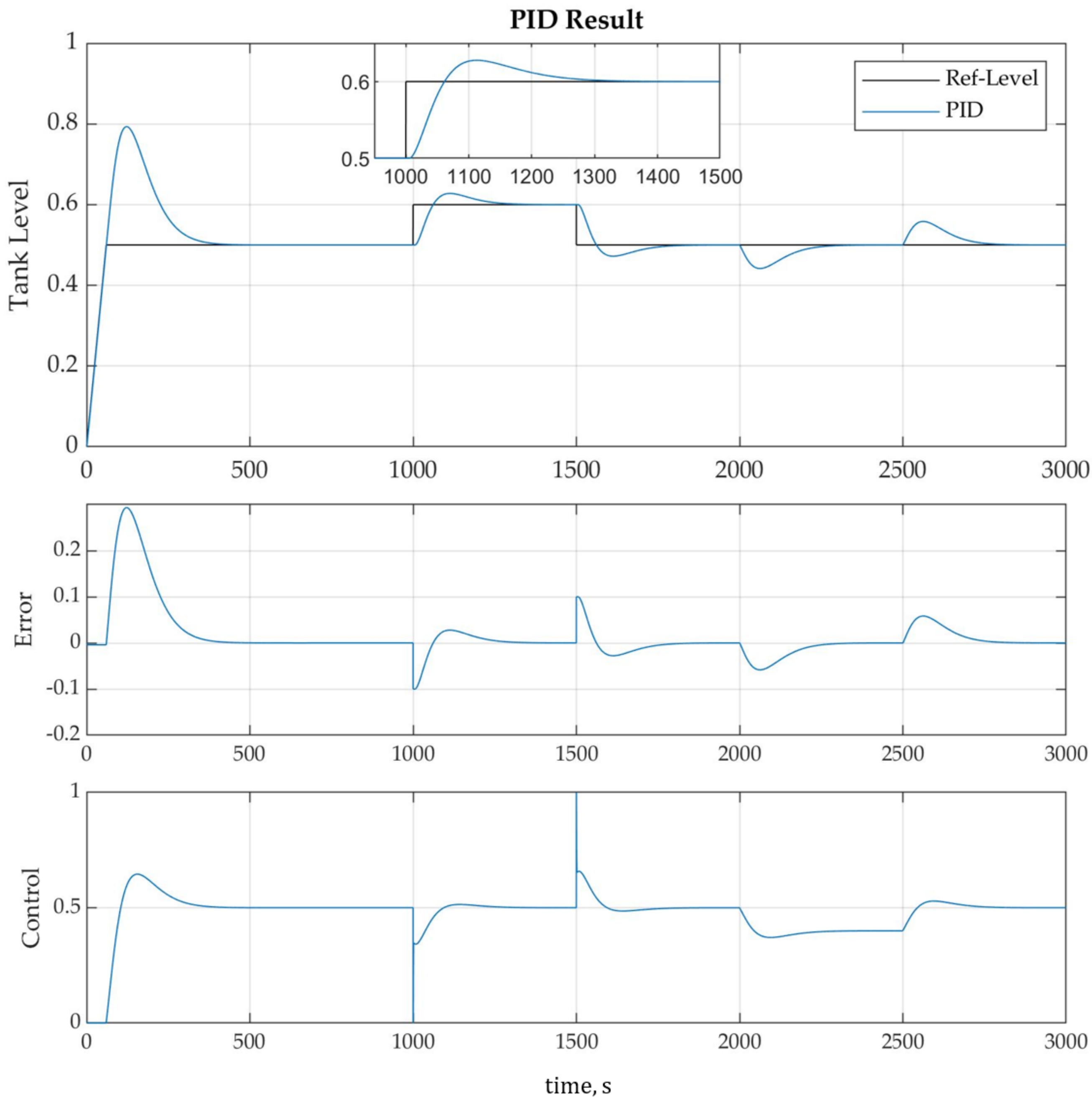


**Figure 13.** Tank level control for PID.

Figure 14 shows the gas cleaning tank system level control variable reference level, together with the results of fuzzy MRAC, MRAC (adaptation rate 0.04), and PID for both MIT and Lyapunov approaches. When the details of the tank level control system response are examined in Figure 14, it is observed that the PID result is very high compared to MRAC results with a given reference signal. It is also seen in the figure that the fuzzy MRAC approach reacts faster to the variable reference level change than the others.

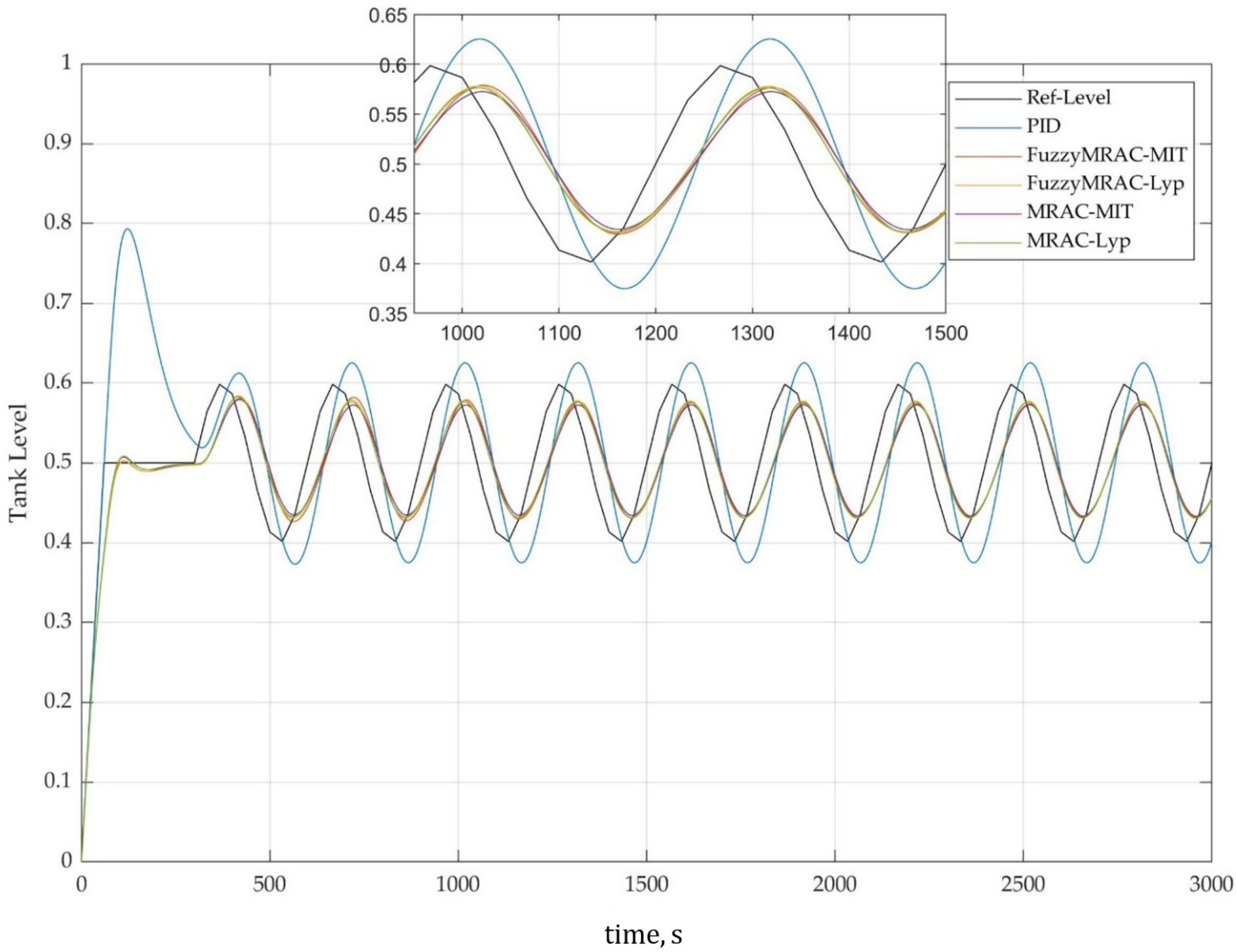


**Figure 14.** Tank level control using fuzzy MRAC, MRAC and PID with variable reference change.

It has been observed that the learning rate of the $\theta$ parameters in the MRAC algorithm varies according to the value of the $\gamma$ learning rate parameter. The slow learning of the $\theta$ parameters caused the MRAC to adapt to the conditions late. Similarly, it has been observed that the fast learning of the $\theta$ parameters causes the MRAC control output to change rapidly and the controlled variable to oscillate.

It is thought that the $\gamma$ value being variable according to the state of the error signal will increase the success of MRAC. Accordingly, MRAC controller $\gamma$ value was determined by fuzzy rules. It has been observed that the level control with the generated fuzzy MRAC is more successful than MRAC and PID. While evaluating the control success, the tank level and control signal values were examined and an evaluation was made. The fuzzy MRAC ensured that the tank level was stable after sufficient learning. In contrast, the PID controller caused some oscillation at the tank level. In some parts of the study, the amplitude of the oscillation reached very low values, but the oscillation was not damped. It was mentioned that in the blast furnace gas cleaning tank level control problem, it is more important to prevent the tank from emptying and overflowing than to keep the tank level constant. According to this information, both controllers can be used to solve this problem. However, when comparing the control signal values, it can be said that fuzzy MRAC is more useful. Because a valve controlled by the control signal of the PID controller oscillates 1.5 times a second for 1 period. This valve works 24 h a day, 7 days a week. Working as a continuous oscillator means that the life of the valve will end in a shorter time than normal. As an alternative solution, if a higher cost valve is used, it may be possible to operate longer without valve failure. Or, according to the results of this study, it will be possible to use the control valve for a longer time by making the washer tank level counter with fuzzy MRAC.

## 5. Conclusions

In this study, the performance of the MRAC in the scrubber tank level control problem of the blast furnace gas cleaning system was investigated. While automation systems used external function hardware even for the use of PID controllers in the past, today they have become able to perform many operations. Automation systems, which have had PID functions in their libraries for years, have added control methods, such as fuzzy logic controller, artificial neural networks, and MPC, to their libraries with the developing technology. This means that MRAC can be easily applied to automation systems. The controller designed for MRAC with a learning coefficient, which is made variable by a method, such as a fixed learning coefficient or a fuzzy logic controller, can be easily coded into the automation system. After cold and hot test procedures, the gas cleaning tank system can be used for level control.

Fixed learning coefficient MIT MRAC and Lyapunov MRAC is compared to PID control. It is seen that the MRAC control performance is better than the PID control performance. However, before using fixed learning coefficient MRAC, a designer needs to make several experiments to determine the correct learning coefficient. Making these kinds of experiments on real world systems, such as a blast furnace or other iron and steel making plants, can be unsuitable. On the contrary, applying variable learning coefficient MRAC on such systems each DCS or PLC control program cycle, a new adaptation calculation is done. According to the simulation results, this continuous adaptation makes MRAC better, compared to PID and fixed learning coefficient MRAC control.

The application of fixed learning coefficient MRAC or variable learning coefficient MRAC to the tank level control problem will bring some advantages. Contrary to the current situation, the need to use a second valve, called the emergency valve, for the control of the gas cleaning tank will be eliminated. In the current situation, the control valves that come from the fully open position to the fully closed position. This large amplitude movements cause wear on the valve. Moving parts of the gate, o-rings, gaskets are negatively affected by this wear and corrosion. Moreover, lifetime of the springs control valve is reduced. These mechanical problems cause control valve failures and reduce mean time between error of control valve. Hence, there is unpredicted gas cleaning tank control system failures causing unplanned blast furnace shut downs.

Applying MRAC to a gas cleaning system water tank control problem, as simulation results show, the oscillation of the control signal send from DCS to the control valve is reduced compared to the PID control. Thus, the oscillation frequency of the control valve and amplitude of the movement are also reduced. This ensures wear and corrosion effects are slower compared to the PID control. In the long term, needed energy is reduced, such as compressed air, hydraulic power or electric energy according to the control valve type to ensure valve movement of the control valve.

The dynamic response of the tank level control system changes when there are some changes in the process, for example, the water flow in the gas cleaning sprays changes over time, sudden fluctuations in the blast furnace pressure, blockages in the pipelines on the inlet and outlet side of the tank, and changes in the control valve characteristic curve due to aging. This change causes the PID controller, which meets the expectations in the old state, to perform poorly in the new state. Decreased controller performance in an industrial facility is undesirable. When such an event occurs, the PID controller parameters need to be recalculated for the new state. When a problem to be experienced during PID design occurs while the facility is in operation, it may cause negativities, such as shutdown of the facility, damage to the equipment due to excessive stress, and decrease in efficiency due to unnecessary raw material consumption. If the control problem is solved using fuzzy based MRAC as an alternative to classical PID, our expectation is that the controller will adapt to changes in the process and will not need repeated parameter adjustment.

In the continuation of this study, MRAC with a fixed or dynamic learning coefficient should be coded in a selected automation system and used in a test setup or in solving a control problem in a low-risk facility.

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