ON THE PROBLEM OF IDENTIFICATION SYSTEM, CONTROLLER DESIGN, REAL-TIME FAULT DETECTION AND DIAGNOSIS FOR WATER SINGLE TANK SYSTEM

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Abstract: The objective of this paper presents an identification of single water tank system by Genetic Algorithm (GA), a comparison control quality of two controllers sliding mode control (SMC) and fuzzy sliding mode control (FSMC) and a design of real-time fault detection and diagnosis for the system. The entire system has been modeled and tested by Matlab/Simulink toolbox.
Keywords: Identification; Sliding Mode Control; Fuzzy Sliding Mode Control; Fault detection; Fault diagnosis

1. Introduction

One of the difficulties encountered in control education consists of providing a theoretical foundation maintaining the practicality. To this aim, experimental labs provide a powerful tool to fill this gap. An experimental lab should be designed to show interesting and industrially relevant control problems which require not too skilled control solutions and real tools, such as instrumentation, control programs, etc.

The single tank system model has proved to be a very interesting system for control education in advanced control courses as well as in research courses.

The problem of controlling the water level of the tank is set so that the water source is used in the most reasonable way to avoid waste. It has since formed the methods of controlling the water level of the tank. Many control methods have been applied such as:

- The research on boiler drum water level control system based on self-adaptive fuzzy-PID [1].
- Water Level Control System Using PLC (Programmable Logic Controller) and Wireless Sensors T20/T21 [2].
- Controlling the water level of the tank using IC (Integrated Circuit), Flip Flop JK and sensor reading the water level value by voltage value [3].
- Design and Implementation of Water Level Control Using Gain Scheduling PID Back Calculation Integrator Anti Windup [4].

The main point of this article is to identify the parameters of the system. After that, we need to monitor and supervised schemes, based on fault detection and diagnosis characterize high efficiency and quality production systems. To achieve such as properties, these structures are based on techniques that allow fault detection and diagnosis in real time. Fault detection and diagnosis provide the root cause and location. Fault detection is based on signal and process mathematical models, while fault diagnosis is focused on systems theory and process modeling. [5]

The paper consists of 5 sections. Part 1 introduces the model and main point of this article. Part 2 presents the mathematical equations. Part 3 shows the design of parameters identification and controller design for single water tanks system. Results on simulation results are presented in part 4. Part 5 presents real-time fault detection and fault diagnosis for the single tank system. Finally, the conclusion is mentioned in part 6.

2. Mathematical Model

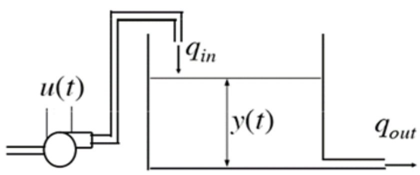

Fig. 1. Schematic representation of the plant

Differential equations describe the dynamics of the tank system [6, pg.201]:

$$\dot{y}(t) = \frac{1}{A(h)}(\mathrm{ku(t)} - \mathrm{aC}_D\sqrt{2gy(t)} \quad (1)$$

$$A(h) = \frac{A_{\max} - A_{\min}}{h_{\max}} h + A_{\min} \quad (2)$$

The system parameters are shown in Table 1:

Tab. 1 Parameters of Single Tank System

Para-meters	**Description**	**Units**
u(t)	Control voltage pump	$0 \leq \mathrm{u(t)} \leq 12\mathrm{V}$
y(t)	The height of water level	cm
A(h)	Cross section of the tank	cm^2
h_{max}	The maximum height of the tank	cm
A_{max}, A_{min}	The minimum cross section and maximum cross section	cm^2
k	Pump power ratio	cm^3/sec
a	Cross section of water drain valve	cm^2
g	Gravitation acceleration	cm/sec^2
C_D	Discharge coefficient	

Equation (2) is a first order nonlinear system. We set state – space variable:

$$x_1(t) = y(t) \quad (3)$$

State-space equation:

$$\begin{cases} \dot{x}(t) = f(x(t), u(t)) \\ y(t) = h(x(t), u(t)) \end{cases} \quad (4)$$

Where,

$$f(\mathrm{x,u}) = -\frac{aC_D\sqrt{2gx_1(t)}}{A} + \frac{k}{A}u(t) \quad (5)$$

$$\mathrm{h(x,u)} = \mathrm{x}_1(t) \quad (6)$$

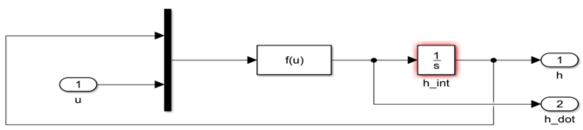

Fig. 2. Simulation on Matlab/Simulink toolbox

3. The design of parameters identification and controller design for single water tanks system

3.1. The design of parameters identification by using genetic algorithm

To solve the problem by GA, we need to perform five important steps are as follow:

Step 1: Determine the parameters that need to be optimized for the system. Thence, randomly generate a population consists of individuals that may or may not be empirical (1 set includes parameters to be optimized).

Step 2: Create an optimal function *J* to evaluate whether the individuals in the population are satisfy with the allowed conditions or not?

Step 3: Select good individuals and remove bad individuals.

Step 4: Based on the selected set of individuals and then crossover to create offspring. After that, based on probability to create mutations for individuals to ensure the search can spread without delay.

Step 5: After running the loop "Selection - Crossover - Mutation" or the optimal condition is satisfied, we need to list down the best individual and end the program.

3.1.1. Linear ranking selection (LRS) [6]

$$p_k = \frac{1}{N}\left[\eta + 2(1-\eta)\frac{k-1}{N-1}\right] \quad (7)$$

Where,

$0 < \eta < 1$, the selection probability of the worst and the best individual is $\frac{\eta}{N}$ and $\frac{2-\eta}{N}$

3.1.2. Crossover BLX- α

The gene C_k of chromosome is selected randomly in $\left[\underline{C_k} \quad \overline{C_k}\right]$:

$$C_k = random\left[\underline{C_k} \quad \overline{C_k}\right] \quad (8)$$

Where,

$$\underline{C_k} = \min(a_k, b_k) - \alpha|a_k - b_k|$$

$$\overline{C_k} = \max(a_k, b_k) + \alpha|a_k - b_k|$$

Fig. 3. Crossover BLX- α method

3.1.3. Non-uniform mutation [6]

$$C_k^{'} = \begin{cases} C_k + \Delta(t, C_{\max} - C_k) & \tau = 1 \\ C_k + \Delta(t, C_{\max} - C_k) & \tau = 0 \end{cases} \quad (9)$$

Where, $\Delta(t,x) = x\left(x\left(1 - r^{\left(1 - \frac{t}{Max\_Gen}\right)^{\beta}}\right)\right)$

r is random value in [0,1] and β is any value

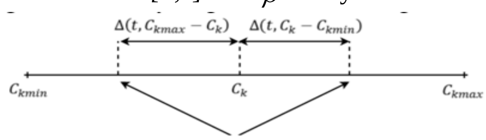

Fig. 4. Non-uniform mutation

3.2. Pseudo Code of GA

1. Initialize multiple sets of initial values:
$\vec{x}_{l,G} = [k_m, a, A, C_D]$
2. Calculate the cost function $J = \|e\|$ with e is the output error compare with the output simulation.
3. For G = 1 to Max_Gene
4. Re-organize the cost function and the sets of values from bad to good.
5. Using linear ranking selection method
6. Using crossover BLX-α method
7. Using non-homogeneous mutation method
8. Calculate the cost fucntion $J(xi,G) = \|e\|$
9. If $J(xi,G,best) \le \epsilon$ then
10. $BREAK$;
11. Else
12. Max_Gen += 1;
13. End if
14. End for

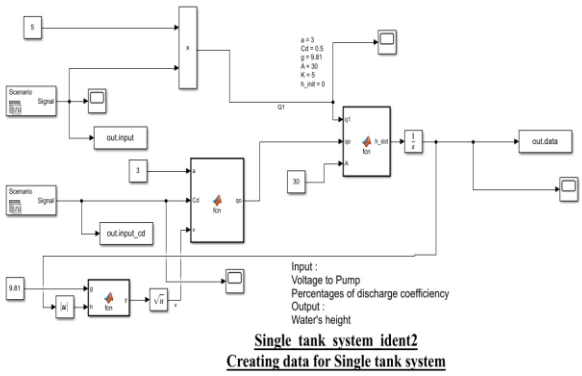

Fig. 5. Simulation program generates sample data for single water tank system

Fig. 5 shows the simulation program which generates the sample data set for identifying parameters: *k*, *A*, *a*. The sample data set consists of input voltage data, the percentage of open valve data, the height of water level data.

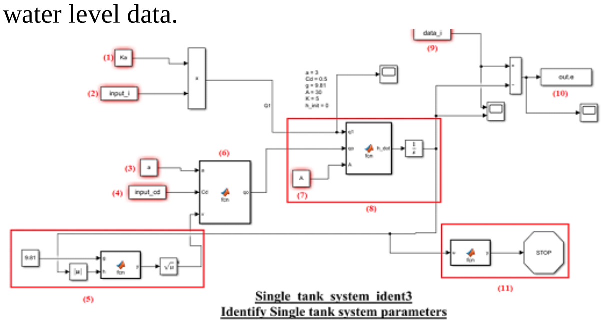

Fig. 6 Matlab program identify parameters of single water tank system

***Tab. 2** The meaning of Fig.6.*

Block	Description
1	Parameter *k* needs to identify
2	The sample data set of input voltage
3	Parameter *a* need to identify
4	The sample data set of the percentage of open valve
5	Equation: $\sqrt{2gy(t)}$
6	The output equation of system: $q_{out}(t) = aC_D\sqrt{2gy(t)}$
7	Parameter *A* needs to identify
8	Equation (1)
9	The sample data set of water level height
10	Parameter *k*, *A*, *a* after identifying
11	The stop condition

3.3. Design of SMC and FSMC for water single tanks system

SMC is applied to stable operation at the set point 5 cm. Besides, chattering is reduced by using fuzzy logic control to operate FSMC structure.

The sliding surface:

$$S = h(t) - h_d \quad (10)$$

where:

$h(t)$ is the actual height of water level

h_d is the set point

Derivative the equation (10):

$$\dot{S} = \dot{h}(t) = \frac{-aC_d\sqrt{2gh(t)}}{A} + \frac{k}{A}u(t) \quad (11)$$

Lyapunov function is selected as:

$$V = S^2/2 \quad (12)$$

$$S \to 0 \Rightarrow \dot{V} = S\dot{S} < 0 \quad (13)$$

We set

$$\dot{S} = -k_{smc}sign(S) \quad (14)$$

, we have

$$\dot{V} = -k_{smc}|S| < 0$$

$$\dot{S} = -k_{smc}sign(S) \Rightarrow \dot{V} < 0 \Rightarrow S \to 0$$

$$\dot{S} = -k_{smc}sign(S) \quad (15)$$

$$\Leftrightarrow \frac{-aC_d\sqrt{2gh(t)}}{A} + \frac{k}{A}u(t) = k_{smc}sign(S)$$

So, the control law is

$$u(t) = \frac{aC_d\sqrt{2gh(t)} - k_{smc}sign(S)}{k} \quad (16)$$

Thence, we design fuzzy rules to eliminate chattering from the system. Fig. 7 depicts the input of the fuzzy rules, and Fig. 8 shows the output of the fuzzy rules. Tab. 3 is fuzzy control rules for single water tank system.

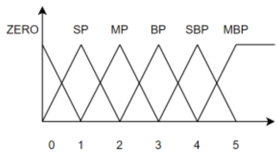

Fig. 7. The input rules

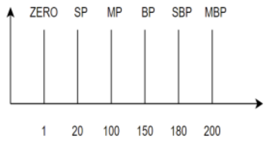

Fig. 8. The output rules

Tab. 3. Fuzzy rules for the single water tank system

Rule	$\vert S \vert$	k_{SMC}
1	ZERO	ZERO
2	SP	SP
3	MP	MP
4	BP	BP
5	SBP	SBP
6	MBP	MBP

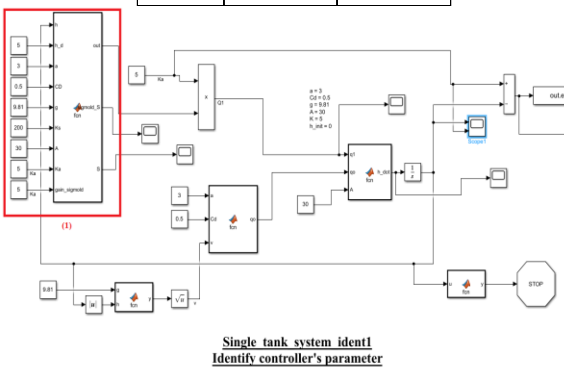

Fig. 9. Simulation of SMC for single water tank

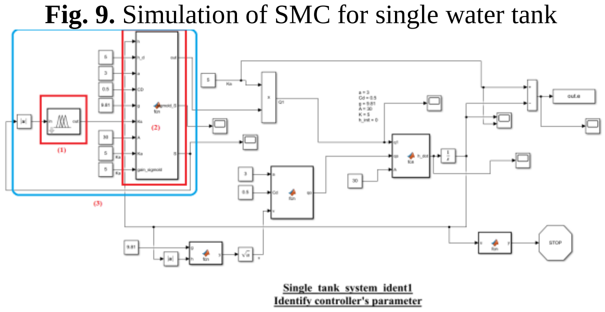

Fig. 10. Simulate FSMC for single water tank

In Fig. 10 Fuzzy logic control block is (1), number (2) is SMC and number 3 is FSMC.

4. Result of simulation

4.1. Parameters identification for single water tank system by GA

By using GA, the authors aim to collect the value of parameters from the real model. In the article, authors simulate the water tank system, then collect input and output data. After that, using GA to identify based on the data with the analyzed model.

Initialize the parameters for GA to train the initialization dataset:

- Population: $N = 50$
- LRS parameter: $\eta = 0.5$
- Crossover BLX-α : $\alpha = 0.5$
- Mutation parameter: $\beta = 0.5$
- Number of trainings: $Max\_gen = 30$
- Crossover probability: $P_c = 0.5$
- Mutation probability: $P_m = 0.5$

After 30 training times, the authors collect new dataset. $J = \| f - f_1 \|$ is erorr between actual data and simulation data.

Tab. 4. The results after training

Parameters			J
A	a	K_a	
28.7644	2.6391	4.6647	3.9430

Compare with the real parameters:

Tab. 5. The real parameters

Parameters			J
A_actual	a_actual	K_a *actual*	
30	3	5	0

4.2. Implementation of SMC and FSMC to single water tank system

- Conditions for SMC:

$$h_{desire} = 5cm, k_{SMC} = \{10 \quad 40 \quad 100 \quad 200\}$$

- $h_{desire} = 5cm, k_{SMC} = 10$

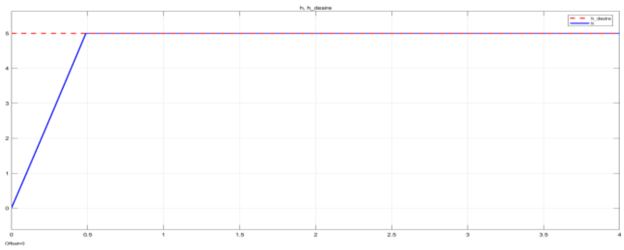

Fig. 10. The output response of the system with $k_{SMC} = 10$ (red: setpoint; blue: height of water in tank)

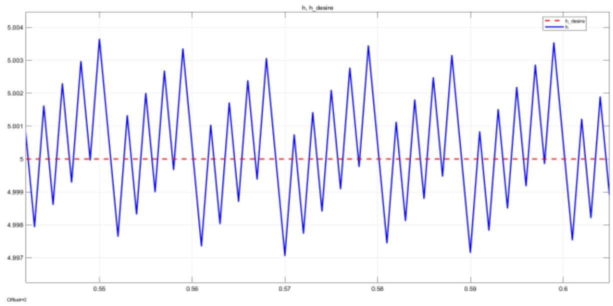

Fig. 11. Zoom-in output response of the system with $k_{SMC} = 10$ (red: setpoint; blue: height of water in tank)

Comment: Response time is 0.5 sec, the system has chattering but small, the chattering frequency is approximately 10ms.

- $h_{desire} = 5cm, k_{SMC} = 40$

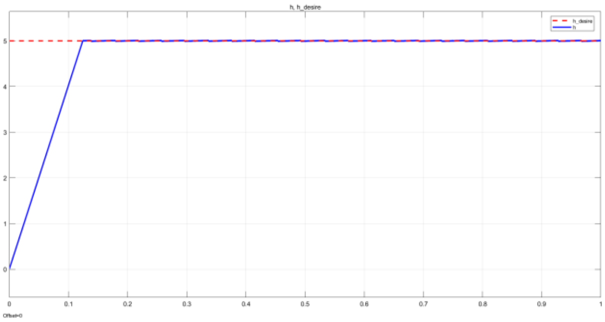

Fig. 12. *The output response of the system* with $k_{SMC} = 40$ (red: setpoint; blue: height of water in tank)

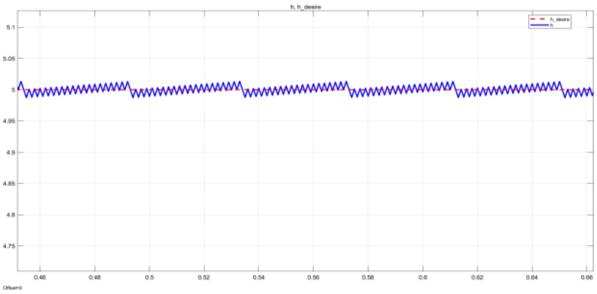

Fig. 13. Zoom-in output response of the system with $k_{SMC} = 40$ (red: setpoint; blue: height of water in tank)

Comment: Response time is 0.12 sec, the system has chattering but it increases, the chattering frequency is approximately 40 ms.

- $h_{desire} = 5cm, k_{SMC} = 100$

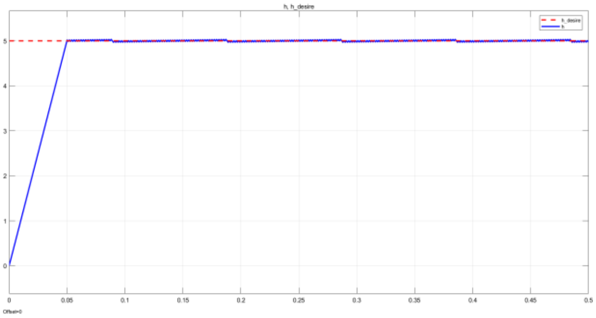

Fig. 14. The output response of the system with $k_{SMC} = 100$ *(red: setpoint; blue: height of water in* tank)

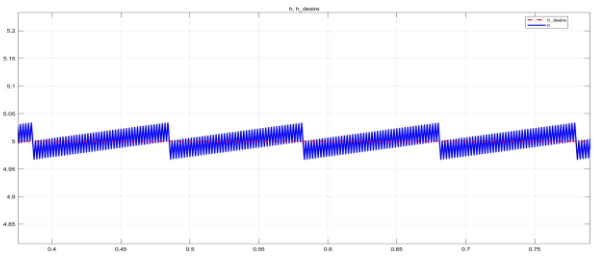

Fig. 15. Zoom-in output response of the system with $k_{SMC} = 100$ (red: setpoint; blue: height of water in tank)

Comment: Response time is 0.05 sec, the system has chattering and the chattering frequency is approximately 100 ms.

- $h_{desire} = 5cm, k_{SMC} = 200$

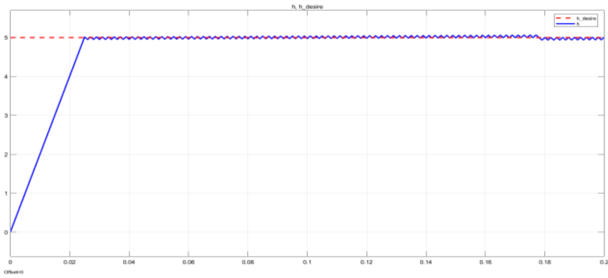

Fig. 16. The output response of the system with $k_{SMC} = 200$ (red: setpoint; blue: height of water in tank)

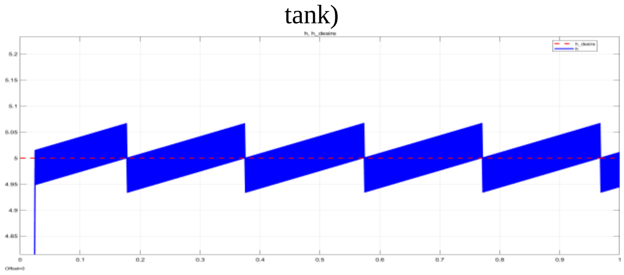

Fig. 17. Zoom-in output response of the system with $k_{SMC} = 200$ (red: setpoint; blue: height of water in tank)

Comment: Response time is 0.22 sec, the system has chattering and the chattering frequency is approximately 200 ms.

- *Condition for FSMC: k_{SMC} will be replaced by Fuzzy logic control.*

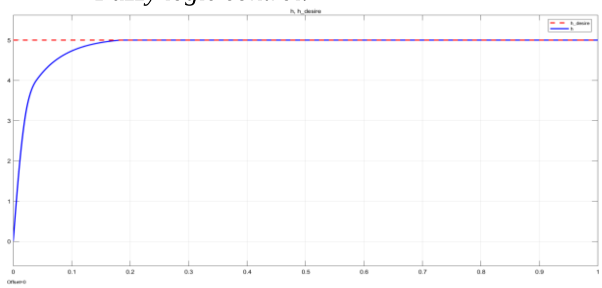

Fig. 18. The output response of the system using FSMC at setpoint h_{desire} = 5 cm (red: setpoint; blue: height of water in tank)

Comment: Response time is 0.2 second, chattering is reduced by using Fuzzy.

5. Real-Time Fault Detection and Fault Diagnosis for the Single Tank System

In this section, a description of the methodology used for the conversion of a monitoring and supervision system in an intelligent system that allows the detection, localization and diagnosis of failures is made possible to take the most appropriate actions to eliminate them and to seek their causes to avoid them. This will improve the efficiency of production systems. [5]

In Fig. 19. , a block diagram is presented where the sequential structure of an intelligent monitoring and supervision system is described at a macro level. This configuration is a technological innovation in the area of intelligent automation. Its implementation is done through computational software of reference that will help in the process of evaluation, detection, location, diagnosis and application of the most appropriate actions in the elimination of a problem or failure. [5]

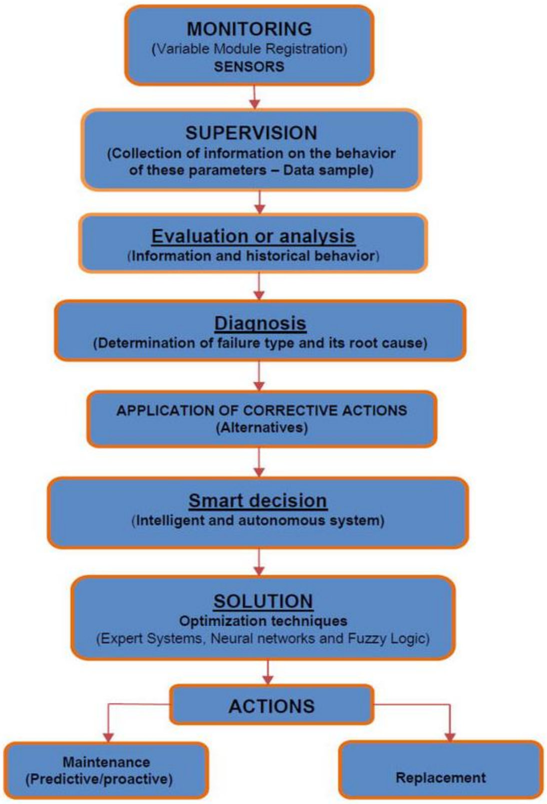

Fig. 19. Flowchart of intelligent monitoring and supervision system. [5]

5.1. Introduction to Intelligent Supervisor

The authors impletement Sliding Mode Observer (SMO) or Utkin Observer to design an intelligent supervisor object for this research. In this approach, the observer system is driven by the control input and by the difference between the output of the observer and the output error is zero. [7]

Consider initially the linear system described by

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (17)$$

$$y(t) = Cx(t)$$

Canonical form – Utkin Observer:

Consider the change of coordinates $x \to T_c x$ whereby

$$T_c = \begin{bmatrix} N_c^T \\ C \end{bmatrix} \quad (18)$$

Where the columns of *Nc 2 Rn*×(*n-p*) span the null space of *C*.

Canonical form for the nominal system:

$$\dot{x}_1(t) = A_{11}x_1(t) + A_{12}y(t) + B_1u(t) \quad (19)$$

$$\dot{y}(t) = A_{21}x_1(t) + A_{22}y(t) + B_2u(t) \quad (20)$$

Where: $T_c x = \begin{bmatrix} x_1 \\ y \end{bmatrix} \begin{matrix} \updownarrow n-p \\ \updownarrow p \end{matrix}$

The observer:

$$\dot{\hat{x}}_1(t) = A_{11}\hat{x}_1(t) + A_{12}\hat{y}(t) + B_1u(t) + L\nu \quad (21)$$

$$\dot{\hat{y}}(t) = A_{21}\hat{x}_1(t) + A_{22}\hat{y}(t) + B_2u(t) - \nu \quad (22)$$

Where: $(\hat{x}_1, \hat{y})$ represent the state estimates, $L \in R^{nx(n-p)}$ is a gain matrix and $\nu_i = M\,\mathrm{sgn}(\hat{y}_i - y_i), M \in R_+$

The error system:

We have: $e_1 = \hat{x}_1 - x_1$, $e_y = \hat{y} - y$

$$\dot{e}_1(t) = A_{11}e_1(t) + A_{12}e_y(t) + L\nu \quad (23)$$

$$\dot{e}_y(t) = A_{21}e_1(t) + A_{22}e_y(t) - \nu \quad (24)$$

Since the pair (*A*; *C*) is observable, the pair (A_{11}; A_{21}) is also observable and *L* can be chosen to make the spectrum of $A_{11} + LA_{21}$ lie in C-.

Define a further change of coordinates by

$$\tilde{T} = \begin{bmatrix} I_{n-p} & L \\ 0 & I_p \end{bmatrix} \quad (25)$$

With $\tilde{e} = e_1 + Ly$, the error system becomes

$$\dot{\tilde{e}}_1(t) = \tilde{A}_{11}\tilde{e}_1(t) + \tilde{A}_{12}\tilde{e}_y(t) \quad (26)$$

$$\dot{e}_y(t) = A_{21}\tilde{e}_1(t) + \tilde{A}_{22}e_y(t) - \nu \quad (27)$$

Where
$$\tilde{A}_{11} = A_{11} + LA_{21}$$
$$\tilde{A}_{12} = A_{12} + LA_{22} - \tilde{A}_{11}L$$
$$\tilde{A}_{22} = A_{22} - LA_{21}$$

In the domain

$$\Omega = \left\{ \begin{matrix} (e_1, e_y) : \|A_{21}e_1\| \\ + \frac{1}{2}\lambda_{\max}(\tilde{A}_{22} + \tilde{A}_{22}^T)\|e_y\| < M - \eta \end{matrix} \right\} \quad (28)$$

Where $\eta < M$ is some small positive scalar. The reachability condition $e_y^T \dot{e}_y < -\eta \|e_y\|$ is satisfied.

An ideal sliding motion will take place on the surface:

$$S_o = \{(e_1, e_y) : e_y = 0\} \quad (29)$$

The corresponding sliding mode dynamics are given by

$$\dot{\tilde{e}}_1(t) = \tilde{A}_{11}\tilde{e}_1(t) \quad (30)$$

Which, by choice of L, represents a stable system and so $\dot{\tilde{e}}_1(t) \to 0, \hat{x}_1 \to x_1(t \to \infty)$

5.2. Design of Fault Detection and Fault Diagnosis for the Single Tank System

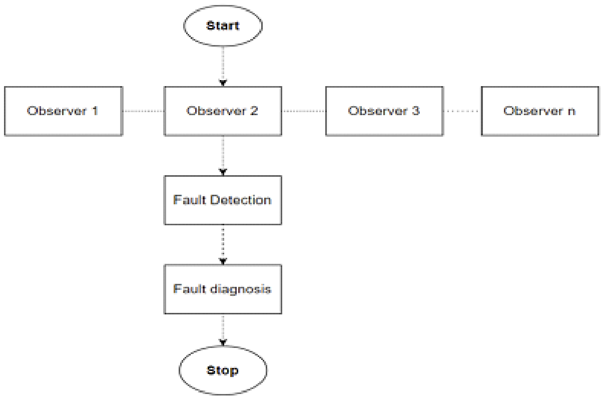

Fig. 20. The diagram of fault detection and fault diagnosis

The observer uses unrelated inputs to find the relevant output, along with the actual sensor signal of this output, we can combine them for more accurate fault diagnosis. In addition, SMO will filter out the noise of the sensor signal as well as the unobserved signals that can still be inferred from the SMO.

The author based on the reliable data set from the combination of observer and fault detection to be able to find and use GA to analyze root cause, location of the problem.

5.3. Apply Fault Detection and Fault Diagnosis for Single Water Tank System

5.3.1. Design of Observer for the Plant

$$\dot{h} = \frac{k * u(t) - a * C_d * \sqrt{2 * g * h(t)}}{A} \quad (31)$$

$$\dot{\hat{h}} = \frac{k * u(t) - K_s * sign(h - \hat{h})}{A} \quad (32)$$

Set $e = h - \hat{h}$

Derivative *e:*

$$\dot{e} = \dot{h} - \dot{\hat{h}} = \frac{-a * C_d * \sqrt{2 * g * h(t)} + K_s * sign(h - \hat{h})}{A} \quad (33)$$

We have $Q_o = a * C_d * \sqrt{2 * g * h(t)}$, so:

$$\dot{e} = \frac{-Q_o - K_s * sign(e)}{A} \quad (34)$$

Using Lyapunov:

$$V = \frac{1}{2}e^2 \quad (35)$$

Derivative V:

$$\dot{V} = \dot{e} * e \quad (36)$$

Let e → 0 so $\dot{V} < 0$ do V > 0

Consider 2 scenarios:

Scenario 1:

$$\begin{cases} e < 0 \\ \dot{e} > 0 \end{cases} \quad (37)$$

Let $\dot{e} > 0 \rightarrow \frac{-Q_o - K_s * sign(e)}{A} = \frac{-Q_o + K_s}{A} < 0 \rightarrow$ (38)

$K_s < Q_o$

Scenario 2:

$$\begin{cases} e < 0 \\ \dot{e} > 0 \end{cases} \quad (39)$$

Let $\dot{e} < 0 \rightarrow \frac{-Q_o - K_s * sign(e)}{A} = \frac{-Q_o - K_s}{A} < 0 \rightarrow$ (40)

$K_s < -Q_o$

From 2 scenarios, we have:

$$K_s < [-Q_o, Q_o] \text{ so } \widetilde{Q_o} \to Q_o \quad (41)$$

5.3.2. Design of Fault Detection

Fault detection block receives signal from observer and actual signal from model to calculate magnitude and rate of change from the input and output values. If the magnitude and rate of change are abnormal, the fault detector will be activated or assigned a fault flag for the system/sensors.

The acceptable conditions for system as given below:

$$|h| < 12m; \left|\frac{dh}{dt}\right| < 50m/s; |Q_o| < 42m^3/s; \quad (42)$$

$$\left|\frac{dQ_O}{dt}\right| < 300\frac{m^3}{s^2}; |Q_i| < 5\frac{m^3}{s}; \left|\frac{dQ_i}{dt}\right| < 300\frac{m^3}{s^2}$$

Tab. 6. The operation of the fault detection and fault diagnosis

Q_i	Q_o	h	Fault Detection	Fault Diagnosis
0	0	0	N/A	N/A
0	0	1	Fault h sensor	N/A
0	1	0	Fault Qo	Activate
0	1	1	Fault h sensor / Fault Qo	Activate
1	0	0	Fault Qi	Activate
1	0	1	Fault Qi/ Fault h sensor	Activate
1	1	0	Fault Qi/ Fault Qo	Activate
1	1	1	Fault Qi/ Fault Qo/ Fault h sensor	Activate

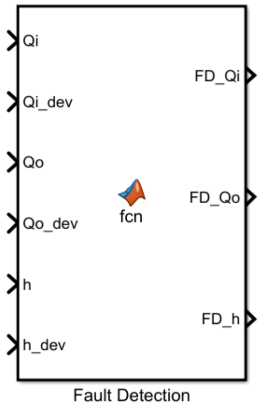

Fig. 21. Matlab block represents for fault detection

5.3.3 Design of Fault Diagnosis

The fault diagnosis is designed based on GA to find the abnormal parameter and then, determine actions for system or sensor. The flow chart of this block is described like Fig. 22.

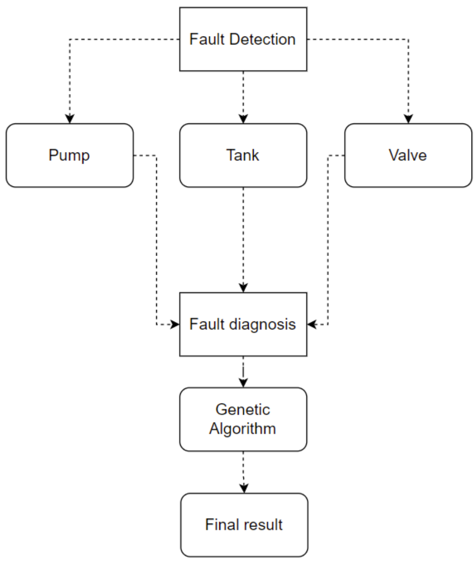

Fig. 22. The diagram of fault diagnosis

The initial error set is deisgned by the authors's experience:

$$e_a = 0.5;\ e_A = 2;\ e_{C_d} = 0.1;\ e_K = 0.05 \qquad (43)$$

The purpose: If the results of GA have error information after training different with the initial error information, there has a change that makes control system biased. Besides, factors make change will be defined.

5.4 Simulation Result

Validation follows (43) and Tab. 6.:

- Code 011:

Q_i	Q_o	h	Fault Detection	Fault Diagnosis
0	1	1	Fault h sensor / Fault Qo	Activate

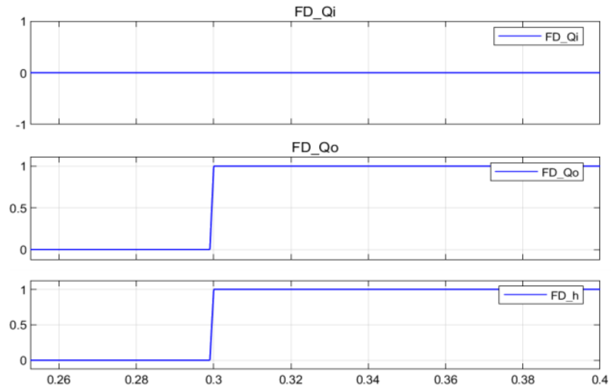

Fig. 23. *The operation of the fault detection and fault diagnosis*

Step 1: The fault detection indicates that there is a problem with the h-sensor.

Step 2: After checking for h-sensor, the fault diagnosis will be activated with the sample data includes unstable factors. The parameter has problem will be defined.

K_{good}	a_{good}	A_{good}	K	a	A	$\lvert e_K \rvert$	$\lvert e_a \rvert$	$\lvert e_A \rvert$
5	3	30	5.0371	2.0552	29.8443	0.0371	0.9448	0.1557

Fig. 24. The results after training by GA

The factor a is reason that makes Q_o changes

Step 3: Need to repair water drain valve

- Code 111:

Q_i	Q_o	h	Fault Detection	Fault Diagnosis
1	1	1	Fault Qi/ Fault Qo/ Fault h sensor	Activate

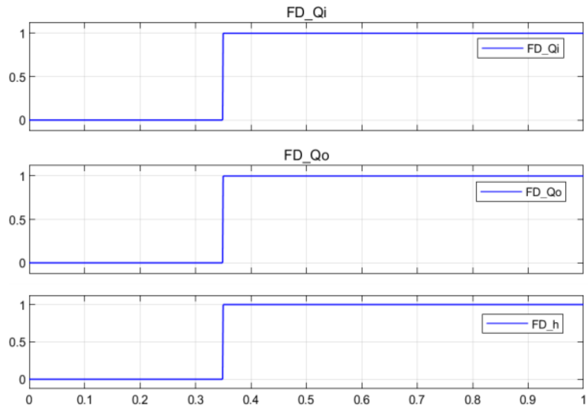

Fig. 25. The operation of the fault detection and fault diagnosis

Step 1: The fault detection indicates that there are problem with the h-sensor, pump and water drain valve.

Step 2: After checking for h-sensor, pump and water drain valve, the GA will be activated with the sample data includes unstable factors. The parameter has problem will be defined

K_{good}	a_{good}	A_{good}	K	a	A	$\|e_K\|$	$\|e_a\|$	$\|e_A\|$
5	3	30	7.0742	3.2846	4.5508	2.0742	1.5508	2.1557

Fig. 26. *The results after training by GA*

Factors *a, K, A* may be reason that make Q_o, Q_i, h change abnormally.

Step 3: Fix or replace sensor.

Step 4: Fix or replace water drain valve.

Step 5: Fix or replace pump.

6. Conclusion

In this study, an identification system uses GA method combined with fault detection and fault diagnosis shows good results since it found the approximately values of the changing variables (which are components damaged and detected by fault detection) of water single tank system. The comparison of 2 controllers shows effectiveness of the advanced controller (FSMC) over the classic one (SMC).

Our future research is control design a real system single tank for validation our simulation.

7. References

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