Fault Detection based on Type 2 Fuzzy Systems for a Single-Rod Electrohydraulic Actuator

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Abstract

Due to their specific features and applications among other industrial systems including mechanical, electrical and pneumatic systems, electro-hydraulic systems have widely been taken into consideration by the scientists and researchers. Because of the fact that an electro-hydraulic system is inherently a nonlinear system, it has some problems such as signals' saturation, nonlinear efficiency, uncertainties caused by the compressibility, internal and external leakages, a dead band of the flow around the zero point, and the adhesion and friction. In this paper, we have focused on fault detection issues in an electro-hydraulic system based on the type-2 fuzzy systems. One of the most important theories proposed for the identification and control of the nonlinear systems is the fuzzy systems' theory. Therefore, in this study and due to the nonlinearity of the electro-hydraulic systems, the use of type-2 fuzzy system of fuzzy systems' theory is proposed. Type-2 fuzzy systems have a better performance capability than type-1 fuzzy systems. In this research, a residual signal generation method has been utilized for fault detection. Using type-2 fuzzy theory, the upper and lower bounds are estimated for the output, and in case of deviating the output graph of the system under control from this estimated band, the occurrence of fault can be detected. Eventually, the simulation results on the system under study determine the capability of the proposed method.

Keywords: Type-2 Fuzzy Systems, Fault Detection, Nonlinear systems, Electro-Hydraulic Systems.

1- Introduction

Electro-hydraulic systems have widely been used in many industrial applications, including automotive industry, locomotives, power systems, and so on. The reason for this wide use is their reliability and rapid response. In recent years, many researches have been done on the electro-hydraulic systems in the fields of state estimation [1], fault detection and identification [1-4] and robust control [5] due to their good control performances. Thus, according to the place of electro-hydraulic systems in different industries, fault identification and detection issue is one of the significant topics that is of great interest to researchers. On the other hand, given that most industrial systems play a vital role in industrial units and the occurred failures will incur high costs to the industrial units; choosing a suitable method to identify and detect the fault seems very important and essential. The meaning of fault in a system, in fact, is an undesired change from the normal and standard state, at least in one of the features or characteristics of the system under control.

In order to apply the fault detection methods and its identification and control correctly, right modeling of the faults is very significant. As a matter of fact, in the modeling of the fault we should have a correct understanding of the physical relationships of the real systems and their mathematical model. There are several reasons for the occurrence of fault in the systems that can be classified into three categories: the faults caused by an incorrect design, the faults caused by malfunctions and faults caused by the wear-out. On the other hand, from the structural viewpoint, faults can occur in three parts: actuator, sensor, and the components of the system under control [6]. Fault in the actuator appears as the loss of total control signal or some part of it. Also, it can be derived from the fracture or disconnection of the coil, or the leakage in hydraulic systems connected to the actuator. Fault in the sensor can appear generally, such as cable disconnection, or partially as an increased noise or through existing some bias in the output of the system. Bias error means that there is always a fixed error between the actual and measured signals. Faults in the components of system under control emerge as a change in the internal parameters of the system, for example changing of the mass due to unintended release of a porter quad-rotor.

Also the evolutionary steps for troubleshooting of the systems can be expressed as fault revelation, fault separation, fault occurrence, fault identification, and fault detection. In fact, fault detection is the revelation, separation and identification of the fault. Each of the stated items can be an appropriate context for the researchers. But in the present study, the objective is the fault detection of a nonlinear system.

In recent years, several methods have been proposed for fault detection. Generally speaking, these methods are classified in three categories: signal-based, model-based, and intelligent methods. In the signal-based methods, usually one or more signals are processed. Since all the signals of a system have certain harmonics in the frequency, the occurrence of a fault can cause a harmonic in some intervals other than the predetermined intervals in the signal. In model-based methods, initially the system state equations are calculated and then using various methods such as parameters estimation, observer design and residual signal generation the system states' variables are estimated regarding certain time intervals. In the intelligent methods of fault identification mainly using neural networks, fuzzy logic, evolutionary algorithms and other intelligent methods, and by combining them with the model-based and signal-based methods, we can address the problem of fault identification in the systems.

In the current study, a model-based method based on the generation of a residual signal has been used for fault detection. In this method, in order to reveal the fault, a signal must be made which shows the presence or absence of the fault. Whenever the created signal is zero, it indicates the absence of the fault and the larger amount of this signal is indicative of a larger fault. In the fault detection method based on the residual signal, a model is considered on the basis of input and output signals and the physical rules governing the system. Residual signal, in fact, is the difference between the original system and the modeled system. Figure 1 shows the overall strategy of the model-based troubleshooting.

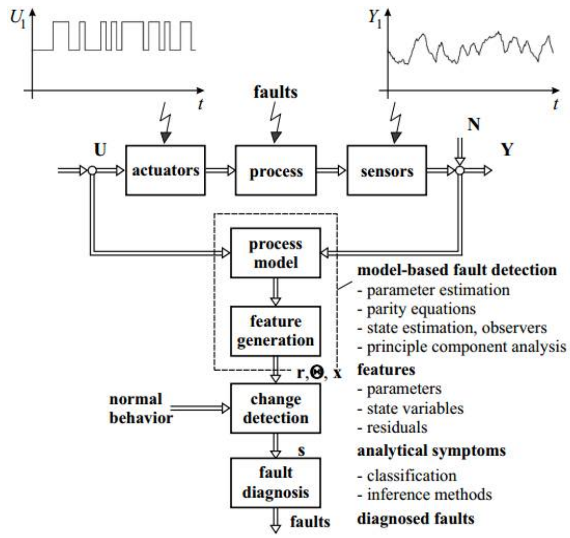

Fig. 1. Model-based troubleshooting scheme [7]

It can be observed in Figure 1 that the first step is related to the creation of a proper model. Then, based on the obtained model and the normal behavior of the system, changes in these cases are evaluated compared to the normal mode.

In order to detect the occurrence of a fault based on the generation of a residual signal, different methods such as nonlinear observers [8-10], adaptive observers [11, 12] and intelligent methods like fuzzy systems [13] have been used. The reason for the researchers' interest to this method for the fault detection is the simplicity in understanding and its implementation in practical applications.

On the other hand, the actual and practical systems are inherently nonlinear, so linear systems are not that efficient to identify nonlinear systems. In this case, the researchers have used nonlinear or intelligent techniques. One of the useful strategies is to use fuzzy systems' theory [14, 15]. Fuzzy systems are the systems with the precise definition and fuzzy control is a special type of nonlinear control. Fuzzy systems due to having membership functions with accurate membership degrees have a limited ability to reduce the uncertainty impact in fuzzy rules. However, the similarity of fuzzy systems to human behaviors, simple calculations and the robustness of this theory are considered as the advantages of this method.

Fuzzy systems can be divided into two categories regarding membership degree: type-1 and type-2 fuzzy systems. Membership function of type-1 fuzzy system takes a value between 0 and 1, is a two-dimensional function, does not include the membership of uncertainty and will allocate a separate membership degree to each input data. Meanwhile, type-2 fuzzy systems have fuzzy membership degrees; thus, these systems are also called fuzzy-fuzzy sets. Professor Zadeh in 1975 showed that type-2 fuzzy systems faced with uncertainties and nonlinear factors work much better than type-1 fuzzy systems [16]. Therefore, in the environments where uncertainty is high, type-2 fuzzy systems are more considerable and usable. Recently, type-2 fuzzy systems have been widely used in system identification [17, 18], fault detection and identification [19, 20], fault control [21-23] and system control [24-26]. Since type-2 fuzzy systems' theory is used in the present paper, in this part those papers have been considered and examined that focus on type-2 fuzzy systems. In [25] a type-2 fuzzy controller has been used to control the direction of the movement and the height of a quad-rotor flying robot. The reason for the use of type-2 fuzzy controller in [25] is expressed as its robustness to environmental conditions and the effects of system's uncertainty and noise in the system performance, and this is shown by comparing the proposed method with type-1 fuzzy controller and PID controller. Authors in [26] have studied the issue of tracking and controlling the torque of mobile robot using type-1 and type-2 fuzzy theories. Reference [13] has addressed to the problem of fault detection in type-2 fuzzy systems with nonlinear sensor and generated a residual signal for fault detection using an observer-based filter. In [27, 28] the problem of fault detection in nonlinear systems based on type-2 fuzzy theory has been studied and the proposed method is simulated for the two-tank system.

In summary, it can be stated that in the present paper the fault detection in a nonlinear system using type-2 fuzzy method has been addressed. The overall structure of the paper is as follows: In part 2, type-2 fuzzy systems will be introduced briefly. Part 3 will express the way of fault detection based on type-2 fuzzy systems. Finally, the nonlinear electro-hydraulic system and also the capability of the proposed method on this system will be examined.

2- Introduction of Type-2 Fuzzy Systems

As mentioned in the previous section, type-2 fuzzy systems were introduced to reduce the effect of uncertainty in the systems. Figure 2 displays the overall structure of a type-2 fuzzy system (for more details see [29]). An interval type-2 fuzzy set can be defined as $\tilde{A}$ with the membership degree $\mu_{\tilde{A}}(x)$ [29] :

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x) | \forall x \in X)\} \qquad (1)$$

In equation (1) we have $0 < \mu_{\tilde{A}}(x) < 1$. We can define $\tilde{A}$ in a different form as below:

$$\tilde{A} = \int_{x \in X} \frac{\mu_{\tilde{A}}(x)}{x} \qquad J_x \subseteq [0,1] \qquad (2)$$

In equation (2), $x \in X$, and J_x are called the primary variable, the secondary variable and the primary membership degree, respectively. It should be noted that all of the secondary membership degrees of $\tilde{A}$ are equal to 1. One the other hand, when all of the secondary membership degrees in a type-2 fuzzy set are equal to 1, type-2 fuzzy set is called the interval type-2 fuzzy set. Since the membership function of a type-2 fuzzy set has three dimensions, in order to have a better visualization of it, drawing the two-dimensional domain is useful, as introduced as the uncertainty effect of type-2 membership function. Because all secondary membership degrees of type-2 fuzzy sets is equal to 1, equation (2) can be rewritten as:

$$\tilde{A} = \frac{1}{FOU(\tilde{A})} \qquad (3)$$

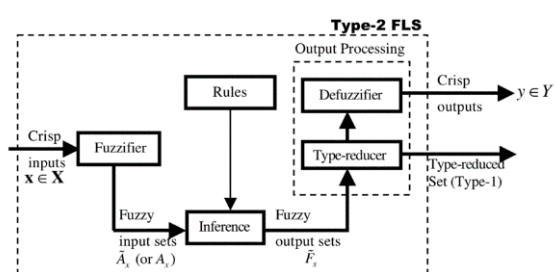

Fig. 2. Structure of type-2 fuzzy controller [29]

In equation (3), FOU specifies the union of all the primary membership functions, and it can be defined as:

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x = \{(x,u) : u \in J_x\} \quad (4)$$

FOU is enclosed between two type-1 fuzzy membership functions determined by the lower and upper membership functions. The effect of uncertainty that is limited by an upper membership function UMF[1] and a lower membership function LMF[2], is shown in Figure 3.

Membership degree of the upper membership function can be displayed by $\bar{\mu}_{\tilde{A}}(x), \forall x \in X$ and the membership degree of lower membership function is displayed by $\underline{\mu}_{\tilde{A}}(x), \forall x \in X$ and

$$\bar{\mu}_{\tilde{A}}(x) = \overline{FOU(\tilde{A})} \quad \forall x \in X \quad (5)$$

$$\underline{\mu}_{\tilde{A}}(x) = \underline{FOU(\tilde{A})} \quad \forall x \in X \quad (6)$$

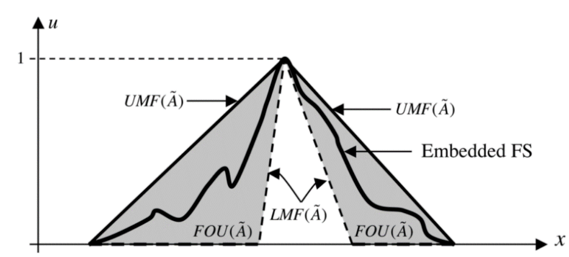

Fig. 3. Interval type-2 fuzzy set [29]

Notice that J_x is an interval set as:

$$J_x = \left\{(x,u) : u \in [\bar{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)]\right\} \quad (7)$$

Now if a rule (i-th rule) is considered for a type-2 fuzzy system with *m* input and one output, it can be rewritten as:

$$R^i : If\ x_1\ is\ F_1^i\ and \dots and\ x_p\ is\ F_p^i\ then\ y\ is\ G^i \quad (8)$$

3- Fault AULT Detection Using Type-2 Fuzzy System

As previously mentioned, the objective of this study is the fault detection of nonlinear systems based on type-2 fuzzy method. In this section, the goal is to evaluate how to model the present nonlinear system based on type-2 fuzzy method and generate a residual signal for fault detection. In the current research, the method of fault detection is a model-based method based on generating a residual signal that is summarized in Figure 1. In fact, in the fault detection method based on generating a residual signal, a confidence bound is created based on the estimated upper and lower bounds for the system output [30].

The estimation of upper and lower bounds is done using type-2 fuzzy systems. In the designing of fuzzy systems in order to estimate upper and lower bounds, input-output data are clustered using a proper fuzzy rule for each cluster [28, 31]. Clustering means partitioning a set of data into some separate subsets in such a way that the data existing in a cluster have some features that distinguish them from the data in other clusters. In this study, initially the input-output pairs are divided into some clusters in terms of the distribution of input points; then input-output clusters are determined using the nearest neighboring clustering algorithm. An appropriate fuzzy rule is used for each cluster. Block diagram of fault detection using type-2 fuzzy system based on generating the residual signal has been shown in Figure 4.

[1] Upper Membership Function (UMF)

[2] Lower Membership Function (LMF)

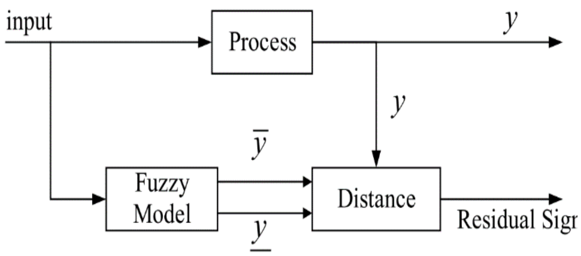

Fig. 4. Block diagram of fault detection using type-2 fuzzy systems

4- Simulation of Electro-hydraulic System

In this part, the nonlinear model of an electro-hydraulic system presented in reference [2] has been examined. Figure 5 displays its overall schematics.

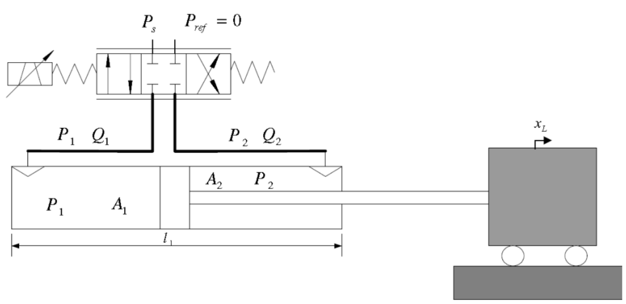

Fig. 5. Schematic of the single-axis electro-hydraulic servo system [2]

The Dynamic model of the intended electro-hydraulic system can be described as follows:

$$m\ddot{x}_L = P_1A_1 - P_2A_2 - b\dot{x}_L - F_{fc}(\dot{x}_L) + \tilde{f} \tag{9}$$

$$\frac{V_1}{\beta_e}\dot{P}_1 = -A_1\dot{x}_L - C_{tm}(P_1 - P_2) - C_{em1}(P_1 - P_r) + Q_1 \tag{10}$$

$$\frac{V_2}{\beta_e}\dot{P}_2 = A_2\dot{x}_L + C_{tm}(P_1 - P_2) - C_{em2}(P_2 - P_r) - Q_2 \tag{11}$$

In the above equations b is the damping coefficient of the model and the adhesion and friction forces. F_{fc} is the modeled coulomb friction, $\tilde{f}$ denotes uncertainties caused by compressibility, $V_i = V_{h_i} \pm A_i x_L, i = 1,2$ is the controllable volume of the first and second cylinders when $x_L = 0$, V_{h_i} indicates the volume of i_{th} chamber, A_i denotes the chamber area (i_{th} piston), β_e is the volumetric coefficient, C_{tm} is the internal leakage coefficient, C_{emi} is the external leakage coefficient, and Q_i denotes the input or output flow rate from the first and second cylinders. The values of all parameters have been presented in references [32] and [33]. Q_1 and Q_2 are the flows derived from the displacement of the electric valve x_v which are specified with the following equations:

$$Q_1 = k_{q_1}x_v\sqrt{\Delta P_1}, \quad \Delta P_1 = \begin{cases} P_s - P_1 \; for \; x_v \geq 0 \\ P_1 - P_r \; for \; x_v < 0 \end{cases} \tag{12}$$

$$Q_2 = k_{q_2}x_v\sqrt{\Delta P_2}, \quad \Delta P_2 = \begin{cases} P_2 - P_r \; for \; x_v \geq 0 \\ P_s - P_2 \; for \; x_v < 0 \end{cases} \tag{13}$$

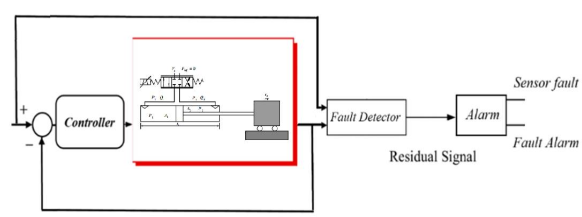

Fig. 6. Electro-hydraulic system in the control loop along with the fault detector and alarm creator blocks

In this paper, x_v has been considered as the control input, then to control the position of a wagon weighting $m = 100$ kg which is connected to a single-axis hydraulic actuator, a simple proportional controller $u = 0.04x_v$ has been used. Figure 6 displays the block diagram of the closed-loop control signal used in electro-hydraulic systems. In this closed-loop system, the proposed controller is a dual-mode proportional controller. When it is needed to move the wagon towards right, cylinder 1 is filled and cylinder 2 is discharged, and contrary when the wagon moves towards left, cylinder 2 is filled and cylinder 1 is discharged.

4.1. Numerical Simulation

As already mentioned, in this paper the model of an electro-hydraulic system has been simulated in the Simulink environment. Position of the wagon connected to the electro-hydraulic actuator is considered as the output. An input signal made up of several rising and falling steps, as shown in Figure 7 has been applied to it and the wagon's position is plotted.

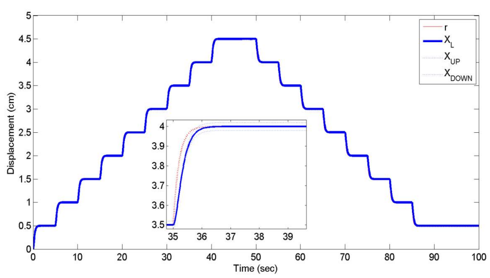

Fig. 7. Displacement graph used in interval type-2 fuzzy identifier

These input-output pairs have been used to identify an interval type-2 fuzzy model in this electro-hydraulic system. Upper and lower limits of the interval type-2 fuzzy system output are shown in the Figure above. These lines are plotted almost 0.2 millimeters upper or lower of the system response. In order to identify the system, sampling time is considered 0.1 milliseconds. So a million data are created in 100 seconds. The first 500000 data are related to the time when the wagon moves towards right and the reference signal increases, and the next 500000 data are caused by the reduction of the reference signal, namely the wagon moves towards left. These data are used to generate the data files. These files contain the information about type-2 fuzzy systems. For them and in both cases of decreasing and increasing the reference signal, a band of 0.2 millimeters is considered for the allowed upper and lower bounds related to the position changes. These files have been used by Matlab functions to create $\hat{y}_{Down}$ and $\hat{y}_{Up}$ signals. These functions have the responsibility of designing the optimal type-2 fuzzy system. Eventually, in Simulink environment a simulator program has been written that consists of some parts for the simulation of electro-hydraulic system, controller and the fault detector (with the aid of type-2 fuzzy system). Figure 8 shows the system response in the presence of various faults that have occurred in the system at different times. Diagrams derived from the magnification of the diagram of Figure 8 are plotted in Figures 9 and 10 again.

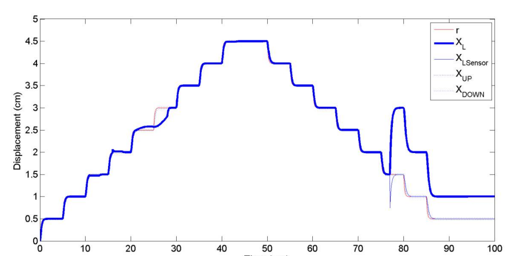

Fig. 8. System response to the reference signal in the presence of all types of faults

In Figures 9-a and 9-b between the seconds 11 to 13 and the seconds 41 to 43, an equal amount of leakage is considered in cylinder 1.

In Figure 9-a, the output of the system under control is got out of the interval assumed by the interval type-2 fuzzy model and the occurrence of fault has been detected. But due to the nonlinear nature of the system under control, in Figure 9-d the fault has less effect on the response of the system under control so the occurrence of fault is not detected (See Figure 11).

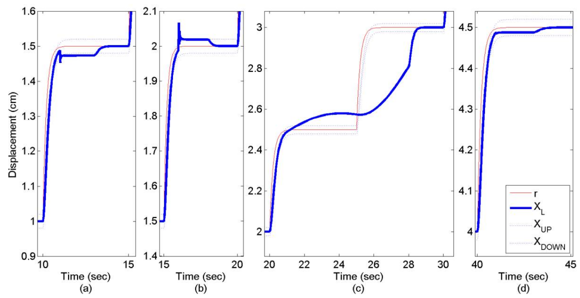

Fig. 9. Magnification of Figure 2 (system response to the reference signal in the presence of all types of faults)

In Figure 9-d, and between the seconds 16 to 18 the same amount of leakage is considered in cylinder 2. This time because of the nonlinear nature of the system under control, the effect of fault occurrence is detected better. In Figure 9-c, at the same time, the occurrence of an equal amount of leakage is assumed in cylinders 1 and 2. In contrast to our imaginations, the simultaneous occurrence of the leakage fault in both cylinders are not neutralized each other's effect, but rather the closed-loop system is barely controlled and has been able to track the desired trajectory. However, according to Figure 11, the occurrence of this fault has also been detected very well. In $t = 50.25\ s$ it is assumed that 30% of the tank pressure has reduced and in $t = 51.5\ s$ it has returned to the initial state.

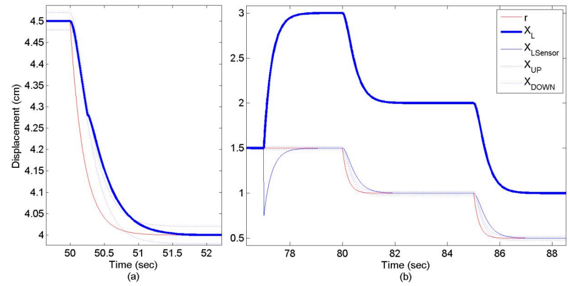

Fig. 10. Magnification of Figure 2 (system response to the reference signal in the presence of all types of faults)

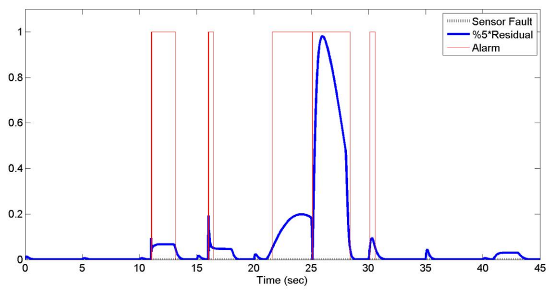

Fig. 11. The first 45 seconds of residual signal and the created alarms

According to the plotted diagram in Figure 12, the occurrence of this fault is also detected in the components of the system under control. Next, it is supposed that in $t = 77\ s$ an event has occurred in the sensor position attached to the moving wagon, so it shows just 50% of the measured value. The change in position is well specified. Given that when there is a fault in the sensor, the residual signal suddenly changes as shown in Figure 12, so if the derivative of the residual signal reaches higher than a certain value, fault detection mechanism must be activated and the alarm must be issued. This time, again, fault detector has been operated very well and the occurrence of fault in the sensor is detected through a specific designed mechanism.

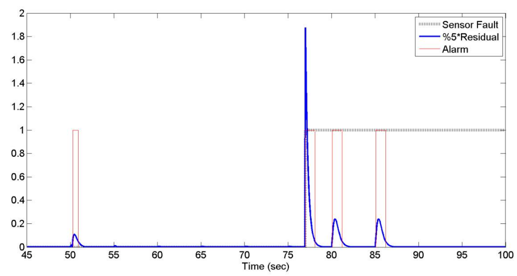

Fig. 12. (Continuation of Figure 5) residual signal and the created alarms

The input (or output) flows of cylinders 1 and 2 are plotted in Figure 13. The created changes during the occurrence of assumed faults are specified well.

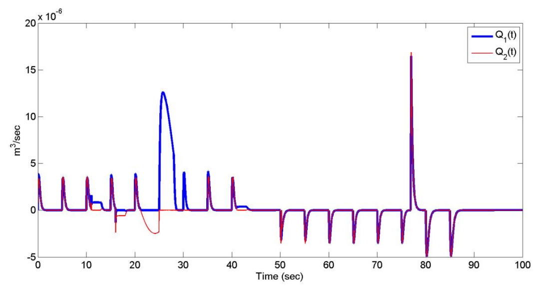

Fig. 13. Diagram of the controlled flow (entering the cylinders 1 and 2)

In Figure, 14 diagram of the controlled pressure in cylinders 1 and 2 is plotted. The observed changes in the pressure diagram is derived from the difference in the inlet and outlet flow of the cylinders. The difference between these two pressures, namely the value of $P_1(t) - P_2(t)$, causes the wagon displacement. During the occurrence of assumed faults, due to the control of wagon's position, the created changes are well specified in the diagram of $P_1(t) - P_2(t)$. The diagram of $P_1(t) - P_2(t)$ is plotted in Figure 14.

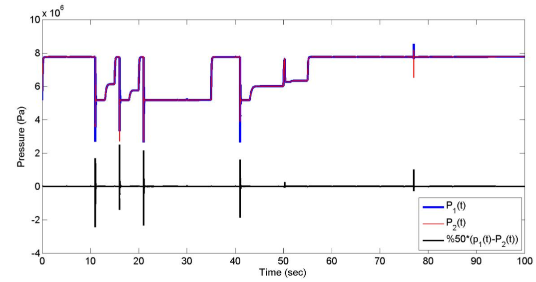

Fig. 14. Diagram of the controlled pressure in cylinders 1 and 2

5- Conclusion

In this paper a new method has been presented for fault detection based on type-2 fuzzy sets. In this method, upper and lower bounds of the type-2 fuzzy system are estimated using optimal fuzzy functions as the confidence bound for the system output. The proposed method was applied on an electro-hydraulic system. The results showed that this method has detected all three types of faults occurred in this system, very well. In the continuation of this work, this method can also be applied on other more complicated systems. Type-2 fuzzy models are used to identify the system and then a narrow interval is obtained for the output signal. Using the upper and lower bounds for this interval, residual signal can be achieved. The results show that this method is well detected with all three types of faults occurred in two-tank system. It should be noted that this method is not proper for the simultaneous detection of the occurred faults. It means that this method is not capable of separating the occurred faults. In order to be able to separate the faults, the future works can be focused on the improvement of this identification method.

References

[1] A. S. Rezazadeh, H. R. Koofigar, and S. Hosseinnia, "Robust leakage detection for electro hydraulic actuators using an adaptive nonlinear observer," *International Journal of Precision Engineering and Manufacturing,* vol. 15, pp. 391-397, 2014.

[2] B. Safarinejadian, B. Bagheri, and P. Ghane, "Fault detection in nonlinear systems based on type-2 fuzzy sets and bat optimization algorithm," *J. Intell. Fuzzy Syst.,* vol. 28, pp. 179-187, 2015.

[3] B. Safarinejadian, P. Ghane, and H. Monirvaghefi, "Fault detection in non-linear systems based on type-2 fuzzy logic," *International Journal of Systems Science,* vol. 46, pp. 394-404, 2015.

[4] B. Yao, F. Bu, J. Reedy, and G.-C. Chiu, "Adaptive robust motion control of single-rod hydraulic actuators: theory and experiments," *IEEE/ASME transactions on mechatronics,* vol. 5, pp. 79-91, 2000.

[5] B. Yao, F. Bu, and G. T. Chiu, "Non-linear adaptive robust control of electro-hydraulic systems driven by double-rod actuators," *International Journal of Control,* vol. 74, pp. 761-775, 2001.

[6] C. Gao, Q. Zhao, and G. Duan, "Robust actuator fault diagnosis scheme for satellite attitude control systems," *Journal of the Franklin Institute,* vol. 350, pp. 2560-2580, 2013.

[7] C. Hwang and F. C. H. Rhee, "Uncertain Fuzzy Clustering: Interval Type-2 Fuzzy Approach to C-Means," *IEEE Transactions on Fuzzy Systems,* vol. 15, pp. 107-120, 2007.

[8] C. Wu, H. Li, H.-K. Lam, and H. R. Karimi, "Fault detection for nonlinear networked systems based on quantization and dropout compensation: An interval type-2 fuzzy-model method," *Neurocomputing,* vol. 191, pp. 409-420, 2016.

[9] C. Wu, H. Li, H.-K. Lam, and H. R. Karimi, "Fault detection for nonlinear networked systems based on quantization and dropout compensation: An interval type-2 fuzzy-model method," *Neurocomputing,* vol. 191, pp. 409-420, 2016.

[10] H. Khan, S. C. Abou, and N. Sepehri, "Nonlinear observer-based fault detection technique for electro-hydraulic servo-positioning systems," *Mechatronics,* vol. 15, pp. 1037-1059, 2005.

[11] H. Li, L. Wu, H.-K. Lam, and Y. Gao, "Fault-Tolerant Control of of Interval Type-2 Fuzzy-Model-Based Systems," in *Analysis and Synthesis for Interval Type-2 Fuzzy-Model-Based Systems*, ed Singapore: Springer Singapore, 2016, pp. 177-199.

[12] H.-M. Chen, J.-C. Renn, and J.-P. Su, "Sliding mode control with varying boundary layers for an electro-hydraulic position servo system," *The International Journal of Advanced Manufacturing Technology,* vol. 26, pp. 117-123, 2005.

[13] H. Li, X. Sun, P. Shi, and H.-K. Lam, "Control design of interval type-2 fuzzy systems with actuator fault: Sampled-data control approach," *Information Sciences,* vol. 302, pp. 1-13, 2015.

[14] I. Ilhan and M. Karakose, "Type-2 fuzzy based quadrotor control approach," in *Control Conference (ASCC), 2013 9th Asian*, 2013, pp. 1-6.

[15] J. P .Tripathi and S. Ghoshal, "Combining inertia and constriction technique in the PSO applied to fault identification in a hydraulic system," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science,*2016.

[16] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning—I," *Information Sciences,* vol. 8, pp. 199-249, 1975.

[17] M. A. Khanesar, E. Kayacan, M. Teshnehlab, and O. Kaynak, "Extended Kalman filter based learning algorithm for type-2 fuzzy logic systems and its experimental evaluation," *Industrial Electronics, IEEE Transactions on,* vol. 59, pp. 4443-4455, 2012.

[18] M. Mendel, R. I. John, and F. Liu, "Interval Type-2 Fuzzy Logic Systems Made Simple," *Trans. Fuz Sys.,* vol. 14, pp. 808-821, 2006.

[19] M. Singh, S. Srivastava, M. Hanmandlu, and J. R. P. Gupta, "Type-2 fuzzy wavelet networks (T2FWN) for system identification using fuzzy differential and Lyapunov stability algorithm," *Applied Soft Computing,* vol. 9, pp. 977-989, 2009.

[20] P. Melin, L. Astudillo, O. Castillo, F. Valdez, and M. Garcia, "Optimal design of type-2 and type-1 fuzzy tracking controllers for autonomous mobile robots under perturbed torques using a new chemical optimization paradigm," *Expert Systems with Applications,* vol. 40, pp. 3185-3195, 2013.

[21] Q. N. Xu, K. M. Lee, H. Zhou, and H. Y. Yang, "Model-Based Fault Detection and Isolation Scheme for a Rudder Servo System," *IEEE Transactions on Industrial Electronics,* vol. 62, pp. 2384-2396, 2015.

[22] R. Isermann, Fault-diagnosis systems: an introduction from fault detection to fault tolerance: Springer Science & Business Media, 2006.

[23] R. Isermann, "Model-based fault-detection and diagnosis – status and applications," *Annual Reviews in Control,* vol. 29, pp. 71-85, 2005.

[24] S. Gayaka and B. Yao, "Fault Detection, Identification and Accommodation for an Electro-hydraulic System: An Adaptive Robust Approach," *IFAC Proceedings Volumes,* vol. 41, pp. 13815-13820, 2008.

[25] S. Oblak, I. Škrjanc, and S. Blažič, "Fault detection for nonlinear systems with uncertain parameters based on the interval fuzzy model," *Engineering Applications of Artificial Intelligence,* vol. 20, pp. 503-510, 2007.

[26] S. Zeghlache, D. Saigaa, and K. Kara, "Fault tolerant control based on neural network interval type-2 fuzzy sliding mode controller for octorotor UAV," *Frontiers of Computer Science,* pp. 1-16, 2016.

[27] Y. Han, S. Oh, B. Choi, D. Kwak, H. J. Kim, and Y. Kim, "Fault detection and identification of aircraft control surface using adaptive observer and input bias estimator," *IET Control Theory & Applications,* vol. 6, pp. 1367-1387, 2012.

[28] Y. Pan, H. Li, and Q. Zhou, "Fault detection for interval type-2 fuzzy systems with sensor nonlinearities," *Neurocomputing,* vol. 145, pp. 488-494, 2014.

[29] Y. Pan and G.-H. Yang, "Fault detection for interval type-2 fuzzy stochastic systems with D stability constraint," *International Journal of Systems Science,* pp. 1-10, 2016.

[30] Y. Pan and G.-H. Yang, "Fault detection for interval type-2 fuzzy stochastic systems with D stability constraint," *International Journal of Systems Science,* pp. 1-10, 2016.

[31] Y. Pan and G.-H. Yang, "Fault detection for interval type-2 fuzzy stochastic systems with D stability constraint," *International Journal of Systems Science,* pp. 1-10, 2016.

[32] Z. Gao, B. Jiang, P. Shi, M. Qian, and J. Lin, "Active fault tolerant control design for reusable launch vehicle using adaptive sliding mode technique," *Journal of the Franklin Institute,* vol. 349, pp. 1543-1560, 2012.

[33] Z. Wang and H. Zhang, "Robust fault diagnosis for a class of nonlinear systems," *Journal of Control Theory and Applications,* vol. 4, pp. 245-251, 2006.