Actuated Hydraulic System Fault Detection: A Fuzzy Logic Approach

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Abstract — **Accurate detection of fault in a hydraulic system is a crucial and equally challenging task. A fuzzy logic topology is developed for the diagnosis of simulated faults in hydraulic power systems. The method proposed is a combination of analytical and fuzzy logic approach. Residuals generated by nonlinear observer are evaluated using fuzzy logic. The fault severity of the system is evaluated based on the membership functions and rule base developed by the fuzzy logic system. This paper demonstrates the use of fuzzy logic as an extension to analytical system to enhance the overall performance of the system. The decision of whether 'a fault has occurred or not?' is upgraded to 'what is the severity of that fault?' at the output. Simulation results showed that fuzzy logic is more sensitive and informative regarding the fault condition, and less sensitive to uncertainties and disturbances.**

Index Terms — **Fault detection, fault severity, fuzzy logic, hydraulic system.**

I. Introduction

Hydraulic systems are very commonly used in industry. Like any other system these systems too are prone to different types of faults. Proportional valves are much less expensive in hydraulic control applications; they are more suitable for industrial environments. Since proportional valves do not contain sensitive, precision components, they offer various advantages over servo valves because they are less prone to malfunction due to fluid contamination. However, these advantages are offset by their nonlinear response characteristics.

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Since proportional valves have less precise manufacturing tolerances, they suffer from performance degradation. The larger tolerances on spool geometry result in response nonlinearities, especially in the vicinity of neutral spool position. Proportional valves lack the smooth flow properties of "critical center" valves, a condition closely approximated by servo valves at the expense of high machining cost. As a result, small changes in spool geometry (in terms of lapping) may have large effects on the hydraulic system dynamics [4]. Especially, a closed-center spool (overlapped) of proportional valve, which usually provides the motion of the actuator in a proportional hydraulic system, may result in the steady state error because of its dead-zones characteristics in flow gain [4]. Fig.1 illustrates the characteristics of proportional valve. Continuous online monitoring of fault in hydraulic system becomes increasingly important day-by-day.

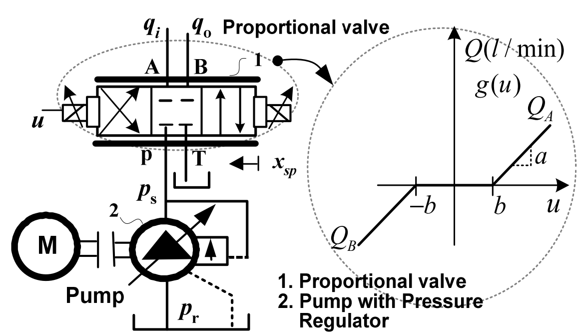

Fig.1 Characteristics of 4/3 closed-center proportional valve

The characteristics of the proportional valve with dead-zones, $g(u)$ is described as follow, fig.1:

$$g(u) = \begin{cases} a(u-b) & \text{if } u \geq b \\ 0 & \text{if } -b \leq u \leq b \\ a(u+b) & \text{if } u < -b \end{cases} \tag{1}$$

where $b, a \geq 0$. a represents the slope of the response outside the dead-zone, while the width of the dead-zone equals 2b.

Remarkable efforts have been devoted to develop controllers. However, PID controllers are not robust to the parameter variation to the plants being controlled. Moreover, it takes time for the automatically self tuned PID controllers to online adapt themselves up to their final stable state.

The fault detection problem can be solved using different approaches like Wald's Sequential Test, as in [4] which is a conventional approach or using innovative approaches like genetic algorithms as in [12], neural networks as in [7], [8], fuzzy logic as in [6] etc. each having its own advantages and disadvantages.

Human experts play central roles in troubleshooting or fault analysis. In power systems, it is required to diagnose equipment malfunctions as well as disturbances. The information available to perform equipment malfunction diagnosis is most of the time incomplete. In addition, the conditions that induce faults may change with time. Subjective conjectures based on experience are necessary. Accordingly, the expert systems approach has proved to be useful. As stated previously, fuzzy theory can lend itself to the representation of knowledge and the building of an expert system. In this paper we used fuzzy logic to detect the severity of fault at the output.

The concept of fuzzy logic was first introduced in 1964 by Professor Lofti Zadeh in [13] which represented the vagueness of human concepts in terms of linguistic variables. After the introduction of fuzzy sets, their applications to solve real world problems were concentrated [2], [11].

Reference [1] concentrates on robust fault detection on an aircraft flight control system. A model based fault diagnosis method for an industrial robot is proposed in [10]. Residuals are calculated by the observer using a dynamic robot model and later evaluated using fuzzy logic.

In this paper we demonstrate a similar *model based* approach for evaluating of severity of fault in the hydraulic actuator using fixed threshold approach, [5]. The *objective knowledge* on the system is represented by mathematical modeling (calculating the residuals using nonlinear observer), [4] while the *subjective knowledge* is represented using fuzzy logic (fuzzy rules and membership functions).

II. System Under Consideration

The schematic of the hydraulic system under consideration, the mathematical model and the design of nonlinear observer can be found in [4]. General nonlinear dynamical systems can be described as follows:

$$\begin{cases} f(x,y,u,t) = A_0 x + Bh(x) + \eta(x) \\ y = C^T x \end{cases} \tag{5}$$

where $h(x) = l(x) + \varphi(x)u + \beta(t-T)\phi(x)$; φ, and l are unknown smooth functions. $x = (x_1, x_2, x_3, ..., x_n)$ is the state vector, $x \in R^n$, u and $y \in R$; $z = \hat{y}$ is the observer output vector; $\eta(x)$ represents the uncertainty in the system dynamics that may include parameter perturbations, external disturbances, noise, etc. All long this study, we consider abrupt fault at time T. As a result, $\beta(t-T)$ is the time profile of failures as shown in fig. 2.

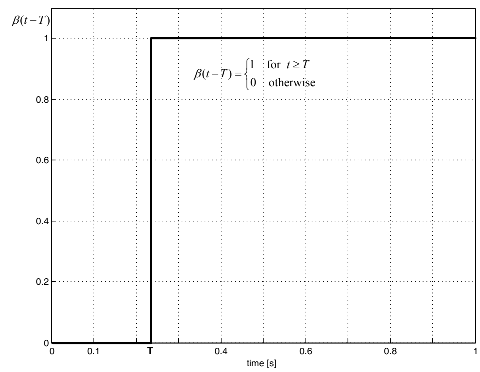

Fig.2 Function $\beta(t-T)$ in (2)

$\phi(x)$ is another function which represent a failure in the system. Mathematical description of the nonlinear observer as follows:

$$\begin{cases} \dot{\hat{x}} = Ax + B\hat{h}(x) + K(y - C\hat{x}) \\ z = \hat{y} = C^T \hat{x} \end{cases} \tag{3}$$

where $\hat{h}(x|\theta_f) = \hat{l}(x|\theta_f) + \hat{\varphi}(x|\theta_f)u + \phi(x|\theta_f)$; K is the observer gain matrix which is selected such as $A = A_0 - KC^T$ is strictly Hurwitz matrix.

In the discrete time system, consider from (2) and (3) $e(k) = y(k) - z(k)$. The actual state of the system y(k) is known through the sensors. The residual e(k) is calculated as follows:

$$e(k) = M_p y(k) - M_p z(k) \tag{4}$$

M_p is an identity matrix of size $m \times n$, $M_p = I_{4\times 1}$

It is perceived that the performance of the actuated system is selected based on four parameters having a range of value from zero (0) to one (1). The elements of the state vector z ≈ $[v\ P_i\ P_o\ x_{sp}]^T$ are: velocity $\dot{x} = v$, input pressure P_i, output pressure P_o and x_{sp} spool displacement. The residual of these four can be measured. In this paper we have concentrated on the *velocity residual* and the identity matrix M_p = [1 0 0 0].

Theoretically, these residuals should be zero under no fault condition. However, in practical context, due to noise, inexact mathematical modeling and system nonlinearity, this residual is never zero even under no fault condition. Reference [4] uses a conventional method called *Wald's Sequential Test* to detect fault. In this method, the cumulative residual error is calculated over a period of time and fault is detected using the fixed threshold concept.

This conventional method has some disadvantages. A value just below the threshold is not considered as a fault while some value just above the threshold will be considered as a fault. This can also lead to missing alarms and false triggers. This information could be potentially misguiding to the operators working on the hydraulic system. This is the drawback of binary logic. The conventional method is rigid and does not consider a smooth transition between the faulty and the no fault condition. The probability assignment procedure is heuristic and depends on the number of Zeros/Ones in the failure signature. This does not give any information about the fault in between the thresholds. In order to take care of this condition we try to replace this binary logic by multi-valued one using fuzzy logic. Evaluating these residuals using fuzzy logic replaces the yes/no decision of fault by the severity of fault at the output.

III. Role Of Fuzzy Logic

From the point of view of human–machine cooperation, it is desirable that faults classification process would be interpretable by humans in such a way that experts could be able to evaluate easily the classifier solution. Another interest of an intelligent interface lies in the implementation of such a system in a control room. Operators have to be informed very quickly if a fault is occurring. They have to understand what exactly the process situation is, in order to make the right counteraction if possible or to stop the system if necessary.

For instance, as shown in fig.3, the fuzzification vector can be assigned to an index of a color map, representing a color code, by defuzzification.

Figure 3depicts the overall architecture of the hydraulic system fault detection where u(t) is the control input. The mapping of the inputs to the outputs for the fuzzy system is in part characterized by a set of *condition* → *action* rules (If-Then) form:

$$\textit{If}\ \text{premise}\ \textit{then}\ \text{consequent} \tag{7}$$

The inputs of the fuzzy system are associated with the *premise*, and the outputs are associated with the *consequent*.

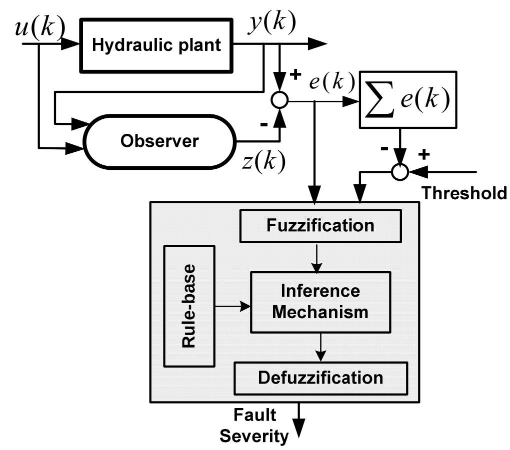

Fig. 3 The structure of Fuzzy fault diagnosis

As already seen, the difference between the expected state z(k) and the actual state of the system y(k) gives the *residual* e(k). The value of residual is added over a period of time which gives the cumulative residual ∑e(k). This value is subtracted from the predicted threshold and is called *cumulative residual difference*. The lower the value of this cumulative residual difference, higher is the fault severity, indicating that the cumulative residual is approaching the threshold and vice versa. The threshold is determined through observations. It will vary depending upon the fault tolerance of the application in which the hydraulic system is used. Even if there is no fault, the modeling errors or noise drive several residuals beyond their threshold. This is usually indicated by all suspect residuals being weak. The *residual* is bounded between the upper and the lower threshold. As soon as it approaches these thresholds, the fault severity increases. Thus, the *residual* and the *cumulative residual difference* are given as two inputs to the fuzzy logic controller. Based on these two inputs, the controller decides the fault severity at the output.

One of the equations of fuzzy equality can be written as:

$$S_{A,B} = \frac{\sum_{i=1}^{n} \min\left\{\mu_A(i), \mu_B(i)\right\}}{\max\left\{\sum_{i=1}^{n}\mu_A(i), \sum_{i=1}^{n}\mu_B(i)\right\}} \tag{6}$$

where n is the dimension number of the discrete space, μ_A is the membership function of fuzzy set A, μ_B is the membership function of fuzzy set B.

Suppose that a fuzzy rule set to be detected F represents the current working class of the actuated hydraulic system, and the other fuzzy reference rule set F_i stands for one working class of the system. Since both the fuzzy reference rule sets and fuzzy rule set to be detected have the same hypersphere subspaces, the equation (6) can be used for their contrasts. As a result, in this study, the approximate measurement of the fuzzy reference rule set F_i can be expressed by:

$$s_i(k) = \frac{|e_i(k)|}{e_i} \tag{8}$$

where $e_i(k)$ *is* the i^{th} residual; $s_i(k)$ is the residual-to-threshold ratio.

Obviously $s_i(k)$ is greater than or equal to 1 if the test is fired on the residual and $s_i(k)$ is less than 1 if it did not.

IV. Design Of Fuzzy Logic Controller

On the one hand, note that fuzzy reference rule sets impossibly cover the whole plant faults; on the other hand, the fuzzy rule set to be detected may bring forward the undefined symptoms which can't be distinguished from fuzzy reference rule sets, as shown in fig. 3. *How can we solve this problem*?

To solve this problem, we include in the evaluation procedure an additional credit degree of unknown classes which is expressed as follows:

$$\varepsilon_{e_i} = 1 - \max_{i=1}^{n}(S_{A,B})$$

Obviously, $0 \le S_{A,B} \le 1$ (9)

A. Inputs

Fig. 4 illustrates the actual and the estimate velocities. The difference is due to the error introduced in the actual system by adding random noise to the *velocity* during simulation.

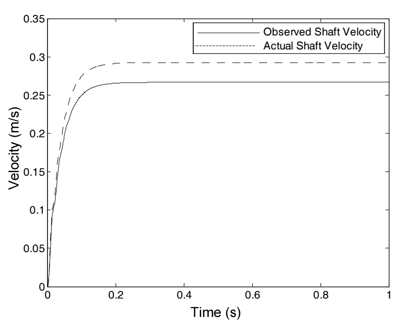

Fig. 4 Graph showing Actual velocity and observed velocity vs time

The plot of residual, cumulative residual, cumulative residual difference along with the thresholds can be seen in the fig. 5 and fig. 6. As seen earlier, the residual and the cumulative residual difference are the two inputs to the fuzzy logic controller.

Fault isolation thresholds are very important parameters; their values are also decided by the statistical analysis of the fault credit degrees (9). As for unknown fault type, consulting fault isolation thresholds are selected upon our knowledge on the system. The detection results of the normal data of the space propulsion system are shown in fig. 5. Because normal credit degree does not exceed the threshold, the detection results are that no fault exists, and working conditions are normal.

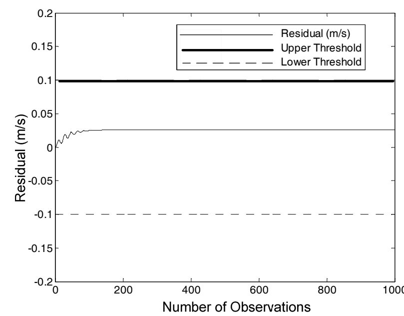

Fig 5. Graph showing 'Residual' along with the upper and lower thresholds vs 'number of observations'

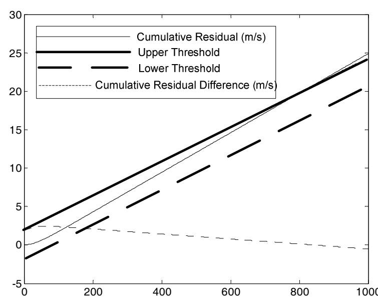

Fig 6. Graph showing the cumulative residual and the cumulative residual difference along with the upper and lower thresholds vs the number of observations

B. Membership Functions

The first input which is residual is divided into 7 membership functions namely, Big Negative (BN), Negative(N), Small Negative(SN), Zero(Z), Small Positive(SP), Positive(P) and Big Positive(BP) shown below.

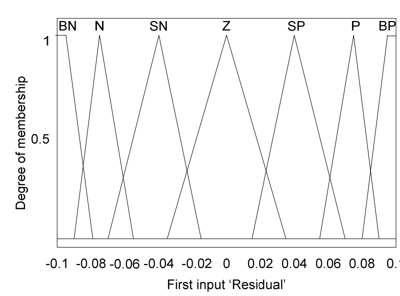

Fig 7. Membership functions for the first input 'Residual'

Similarly, we developed 5 membership functions for the second input which is cumulative residual difference. They are Large Negative(LNeg), Medium Negative(MNeg), Small Negative(SNeg), Zero(Zero) and Positive(POS) as seen in the following fig.

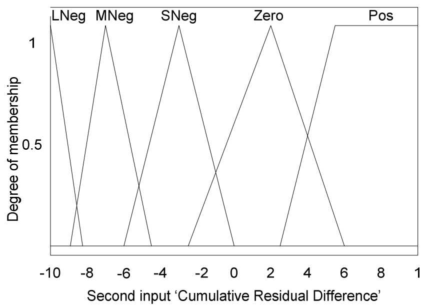

Fig 8. Membership functions for the second input 'Cumulative Residual Difference'

As already seen there are 4 parameters which can be used to calculate the residuals. Among them the *velocity* is the most concerned parameter in this case of study. Hence, the *velocity residual* is selected to determine the fault severity at the output.

The membership functions for the output i.e. fault severity are F0, F1, F2, F3, F4, F5 and F6 where F0 represents the lowest fault severity and F6 represents the highest fault severity. The shapes of the membership functions which are triangular and trapezoidal were selected based on the simple guidelines suggested in [3]. This can be seen in the following fig.

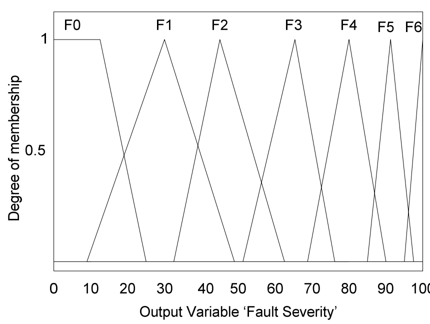

Fig 9. Membership functions for the output 'Fault Severity'

C. Rule Based Inference

Inference rules were developed which relate the two inputs to the output. They are summarized in the Table I. As seen from the table, there are in all 35 rules. For example, if the residual is Big Positive (BP) and the cumulative residual difference is Large Negative (LNeg) then the output fault severity is the highest (F6). Similarly, if the residual is Zero (Z) and the cumulative residual difference is Positive (Pos) then the output fault severity is the lowest (F0).

TABLE I: RULE BASED INFERENCE

Cumulative Residual Difference ->	Residual ->							
		BN	**NEG**	**SN**	**Z**	**SP**	**POS**	**BP**
	Pos	F3	F2	F1	F0	F1	F2	F3
	Zero	F4	F3	F2	F1	F2	F3	F4
	SNeg	F5	F4	F3	F2	F3	F4	F5
	MNeg	F6	F5	F4	F3	F4	F5	F6
	LNeg	F6	F6	F5	F4	F5	F6	F6

D. Defuzzification

After converting the crisp information into fuzzy the last step is to reverse that. Converting the fuzzy information to crisp is known as defuzzification. The center of area/centroid method was used to defuzzify these sets which can be represented mathematically as follows:

$$\textit{Defuzzified value} = \frac{\Sigma f_i \bullet \mu(f_i)}{\Sigma \mu(f_i)} \tag{10}$$

Where *fi* is the fault severity at the output and μ(*fi*) is the output membership function.

E. Rule Viewer

The rules can also be seen from the rule viewer using the fuzzy logic toolbox in MATLAB software. When the residual is 0.01, it is far away from both the upper and lower thresholds (almost at the center) and hence, has lower fault severity. Also, the cumulative residual difference is 9 which means the difference between the actual value of cumulative residual and threshold is high i.e. cumulative residual is far away from the threshold. Hence, the fault severity should be low. A combination of these values of residual and cumulative residual gives fault severity percentage of 9.96% which is low. Similarly, when the residual is 0.089 it indicates that it is very close to the threshold. A cumulative residual difference of -9 indicates that the threshold has been already crossed by the cumulative residual (hence it is negative). Both of these conditions lead to a very high fault severity of 98.4%. This can be seen with the help of the rule viewer facility in the fuzzy logic toolbox. These examples are shown in fig. 10 and fig. 11 respectively with the help of rule viewer.

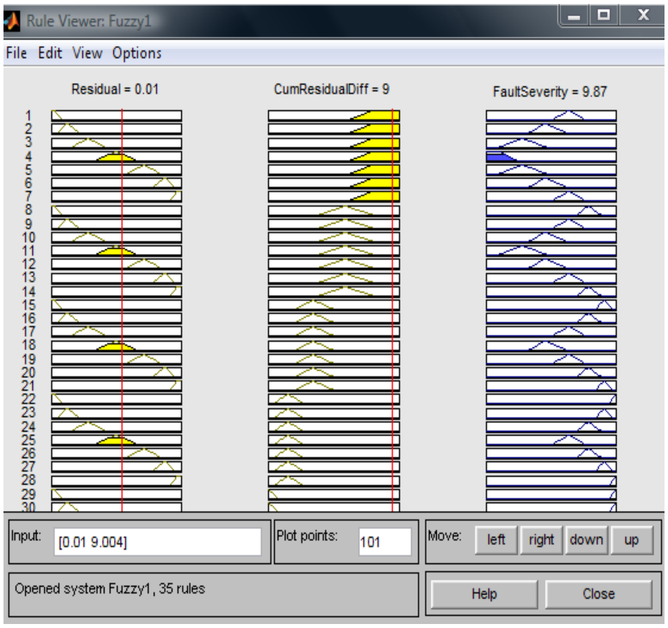

Fig. 10 Test Results for low fault severity

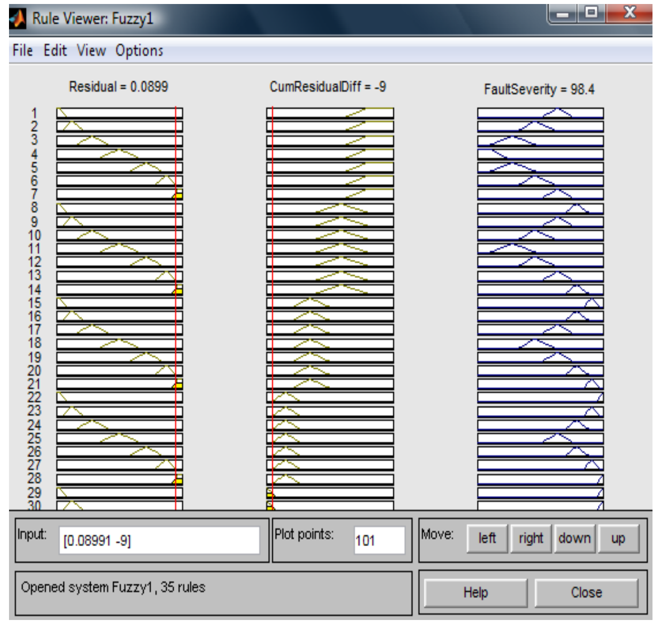

Fig. 11 Test results for high fault severity

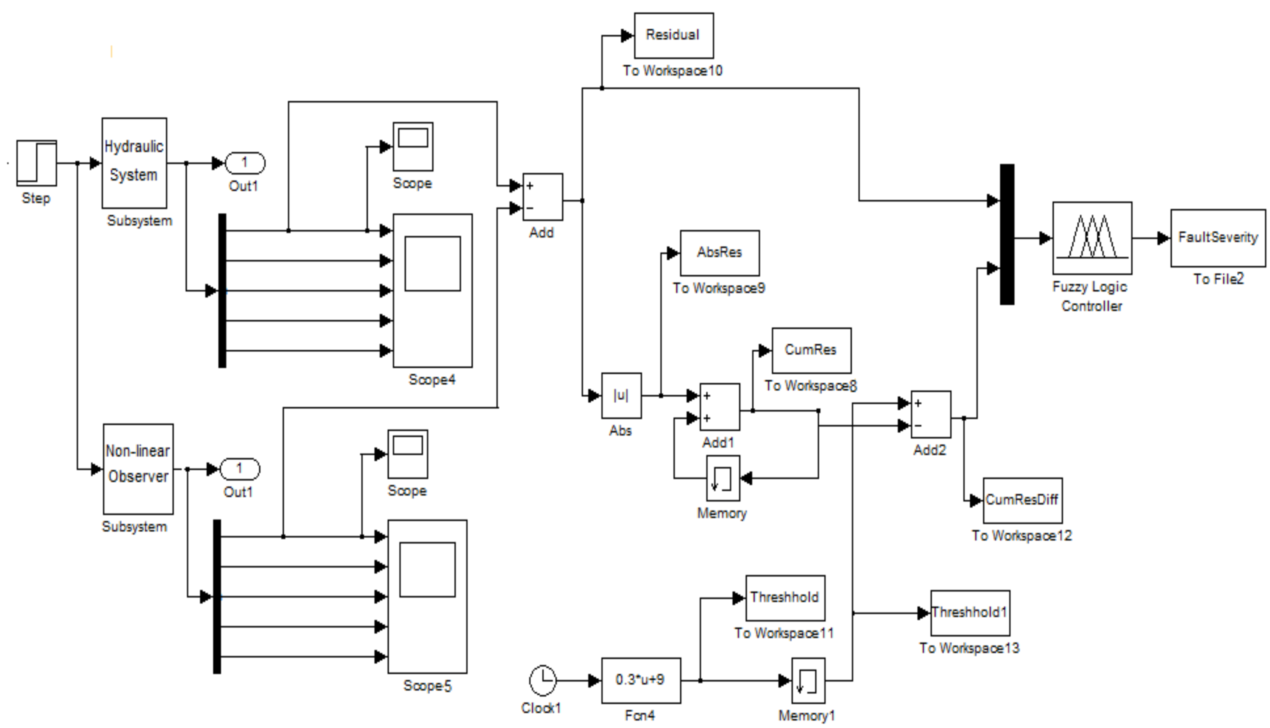

Fig 12. MATLAB/SIMULINK mode

V. SIMULATION

This simulation was carried out in MATLAB SIMULINK using fuzzy logic controller from the fuzzy logic toolbox as shown in fig. 12. The upper subsystem represents the actual system (actual state of the hydraulic system) and the lower subsystem is the nonlinear observer (which predicts the state of the system). The SIMULINK diagram is the implementation of the block diagram shown in fig. 1. The simulation is carried out for a unit step input. Fault is introduced in the actual system by adding noise to the *velocity* in the actual system and different fault severities are tested at the output.

VI. CONCLUSION

The main goal here was to provide maintenance engineers continuous online information about the systems health which would guide them to make decisions. This information needs to be given at an incipient stage in order to avoid any further serious damage to the system. This also helps in avoiding false triggers and missing alarms. This work shows that fuzzy logic when used in combination with analytical methods like non linear observer can enhance the output. It acts as a good extension to upgrade the system

With the fuzzy match results between the fuzzy rule set to be detected and fuzzy reference rule sets, diagnosis logic module automatically judged whether the plant working condition is normal or not. Moreover while fuzzy rule sets are set up, the fuzzy reference rule set generated is used for representing the normal working condition, which is supposed to be the first fuzzy reference rule set.

Simulation results showed what we all know: whatever fault type the plant generates, its symptoms always depart from the characteristics of the fuzzy reference rule set standing for the normal working condition. And thus, with the credit degree representing the normal working, we judged whether the plant working condition is normal, further obtain the fault degree. This study helped to assure that the plant fault existed and to report the system conditions. Future work will be developed to identify the fault type and predict the equipment remaining life.

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