Fault Detection in Hydraulic System Using Fuzzy Logic

Manali Kulkarni, Seraphin C. Abou, and Marian Stachowicz

***Abstract*— Accurate detection of fault in a hydraulic system is a crucial and equally challenging task. The method proposed here is a combination of analytical and fuzzy logic approach. Residuals generated by non-linear 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. More importantly, simulation results demonstrate how fuzzy logic is advantageous over the conventional method by being more informative regarding the fault condition and being more sensitive to faults 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. A fault can be defined as deviation from the normal or expected. In a hydraulic system, the system malfunction is caused due to the changes in the system parameters which is in turn caused due to changes in the environmental conditions, faulty sensors and internal and external fluid leakages.

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Manali Kulkarni is a research assistant with the University of Minnesota Duluth, 1305 Ordean Ct, Duluth, MN 55812, USA (phone: 1-(952)693-5803; e-mail: kulka056@d.umn.edu).

Seraphin Abou is with the Mechanical and Industrial Engineering Department, University of Minnesota, Duluth, 1305 Ordean Ct, Duluth, MN 55812, USA. (e-mail: sabou@d.umn.edu).

Marian Stachowicz is a professor and Jack Rowe Chair with the Electrical and Computer Engineering Department, University of Minnesota, Duluth, 1023 University Dr, Duluth, 55812, MN, USA, (e-mail: mstachow@d.umn.edu).

Faults can be categorized into two types: Firstly, partial fault failure where the system can continue to operate even if there is a small amount of fault and secondly total fault failure where the system needs to be shut down. The fault tolerance will depend totally on where the hydraulic system is used. It will be low if the system is being used in a precision required area like in an aircraft. On the other hand, it will be high if the system is being used in a heavy duty vehicle such as an excavator.

Continuous online monitoring of fault in hydraulic system is becoming increasingly important day-by-day. It is crucial to provide correct information regarding the systems health to the operators. This should be done as quickly as possible in order to guide them to fix the problem. The fault severity of the system at the output is one such crucial information provided to the operators.

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 [11], neural networks as in [6],[8], fuzzy logic as in [5] etc. each having its own advantages and disadvantages. In this paper we used fuzzy logic to detect the severity of fault at the output. Fuzzy logic has several advantages like less modeling complexity and ability to translate human reasoning using linguistic variables. This makes it possible to take into account the uncertainties and nonlinearities otherwise very difficult to model mathematically. In the last several years there has been significant growth in the number of fuzzy logic applications especially in the realms of consumer products, intelligent control applications and fault detection.

The concept of fuzzy logic was first introduced in 1964 by Professor Lofti Zadeh in [12] 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], [10].

Diagnosis of faults in motors using fuzzy logic can be seen in [5], [7]. Detection of stator winding fault in induction motor is presented in [5]. The currents in the 3 respective windings are the inputs which are linguistically described as *very small, small, medium and large*. The output is the condition of motor i.e. *good, damaged or seriously damaged* is also expressed in linguistic terms. The knowledge is represented in terms of membership functions and rules obtained from analytical study, motor performance, simulated data and the engineer's experience. Model simulation carried out in the SIMULINK environment using the fuzzy logic controller can also be seen.

A model based fault diagnosis method for an industrial robot is proposed in [9]. Residuals are calculated by the observer using a dynamic robot model and later evaluated using fuzzy logic. The paper addresses the problem of false triggers and missing alarms which occurs when the residual which is slightly below the predefined threshold has no effect. However, a small increase in the value of residual (which may be due to measurement in noise) triggers an alarm. This problem is addressed based on the adaptive threshold concept using fuzzy logic.

Reference [1] concentrates on robust fault detection on an aircraft flight control system. Robust l_1 estimation technique is used to calculate residuals which are then evaluated using fuzzy logic and fixed threshold approach. The aim of *robust* fault detection system is to be sensitive to faults and insensitive to disturbances and uncertainties at the same time.

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

II. System Under Consideration

The schematic of the system under consideration, the mathematical model and the design of nonlinear observer can be seen in [4]. Using the mathematical equations, the nonlinear observer predicts the next state of the system given the estimate state which is denoted as z(k) in the discrete time system. The actual state of the system y(k) is known through the sensors. The residual e(k) is calculated as follows

$$e(k) = M_p * y(k) - M_p * z(k) \tag{1}$$

M_p is an identity matrix of size $m \times n$, $M_p = I_{4\times1}$

It is perceived that the performance of the actuator is selected based on four parameters. In this study, note that each parameter has 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 v, input pressure P_i, output pressure P_o and x_{sp} spool displacement. This means we can get these four residuals respectively. In this paper we have concentrated on the *velocity residual* keeping 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

The block diagram for the overall system is as shown below where u(t) is the control input.

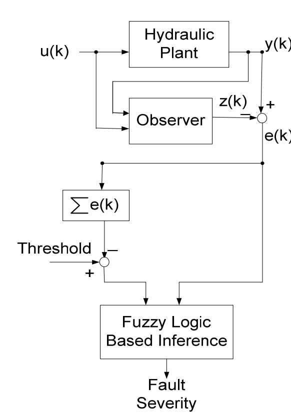

Fig 1. Block Diagram

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 predecided 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.

With the test threshold for the i^{th} residual denoted as , $e_i(k)$ the residual-to-threshold ratio $s_i(k)$ may be obtained as:

$$s_i(k) = \frac{|e_i(k)|}{e_i} \tag{2}$$

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

A. Inputs

Fig. 2 illustrates the actual and calculated velocities. The difference is due to the error introduced in the actual system by adding random noise to the *velocity* during simulation.

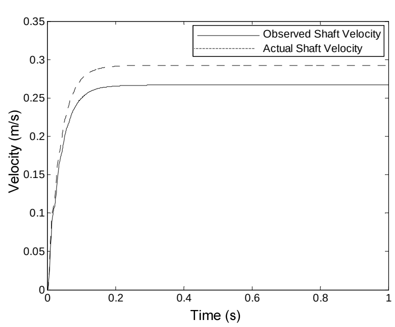

Fig 2. Graph showing Actual velocity and observed velocity vs time

The plot of residual, cumulative residual, cumulative residual difference along with the thresholds can be seen in the fig. 3 and fig. 4. As seen earlier, the residual and the cumulative residual difference are the two inputs to the fuzzy logic controller.

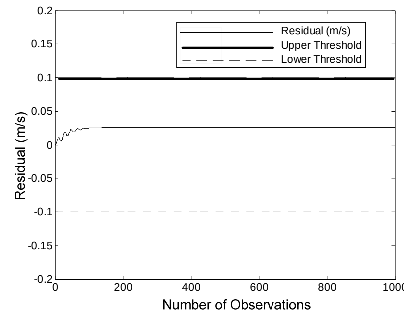

Fig 3. Graph showing 'Residual' along with the upper and lower thresholds vs 'number of observations'

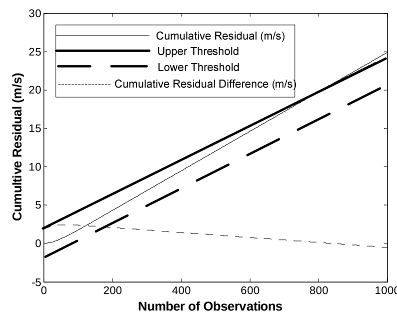

Fig 4. Graph showing the cumulative residual and the cumulative residual difference along with the upper and lower thresholds vs the number of observations

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.

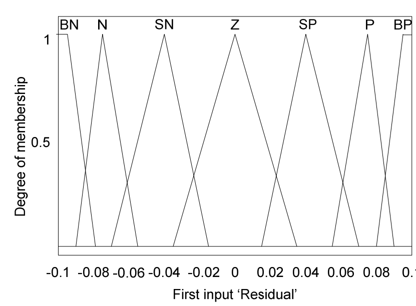

Fig 5. Membership functions for the first input 'Residual'

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.

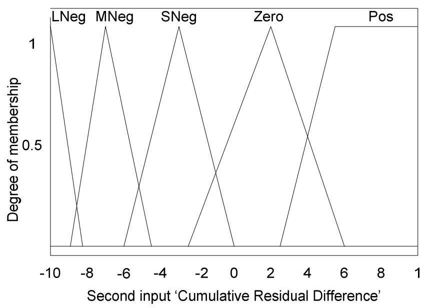

Fig 6. Membership functions for the second input 'Cumulative Residual Difference'

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.

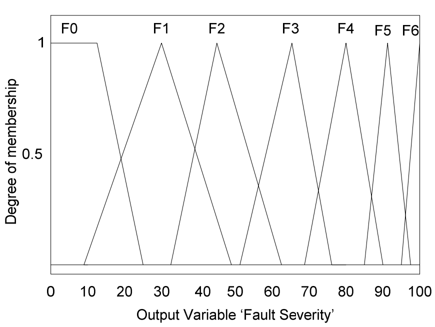

Fig 7. Membership functions for the output 'Fault Severity'

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:

$$\textit{Defuzzified value} = \frac{\Sigma f_i \bullet \mu(f_i)}{\Sigma \mu(f_i)} \quad (3)$$

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. 8 and fig. 9 respectively with the help of rule viewer.

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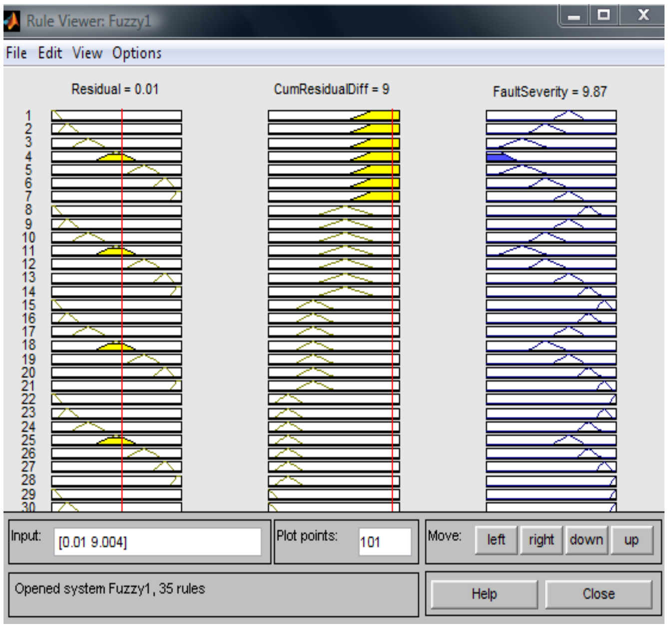

Fig 8. Test Results for low fault severity

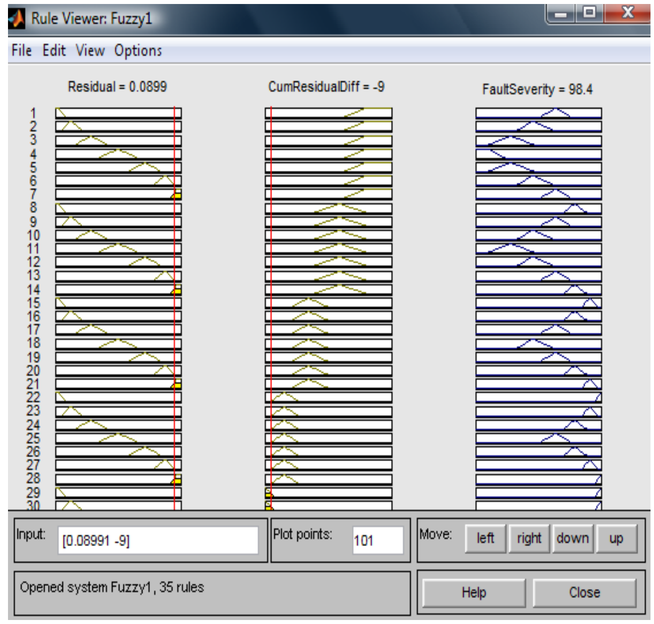

Fig 9. Test results for high fault severity

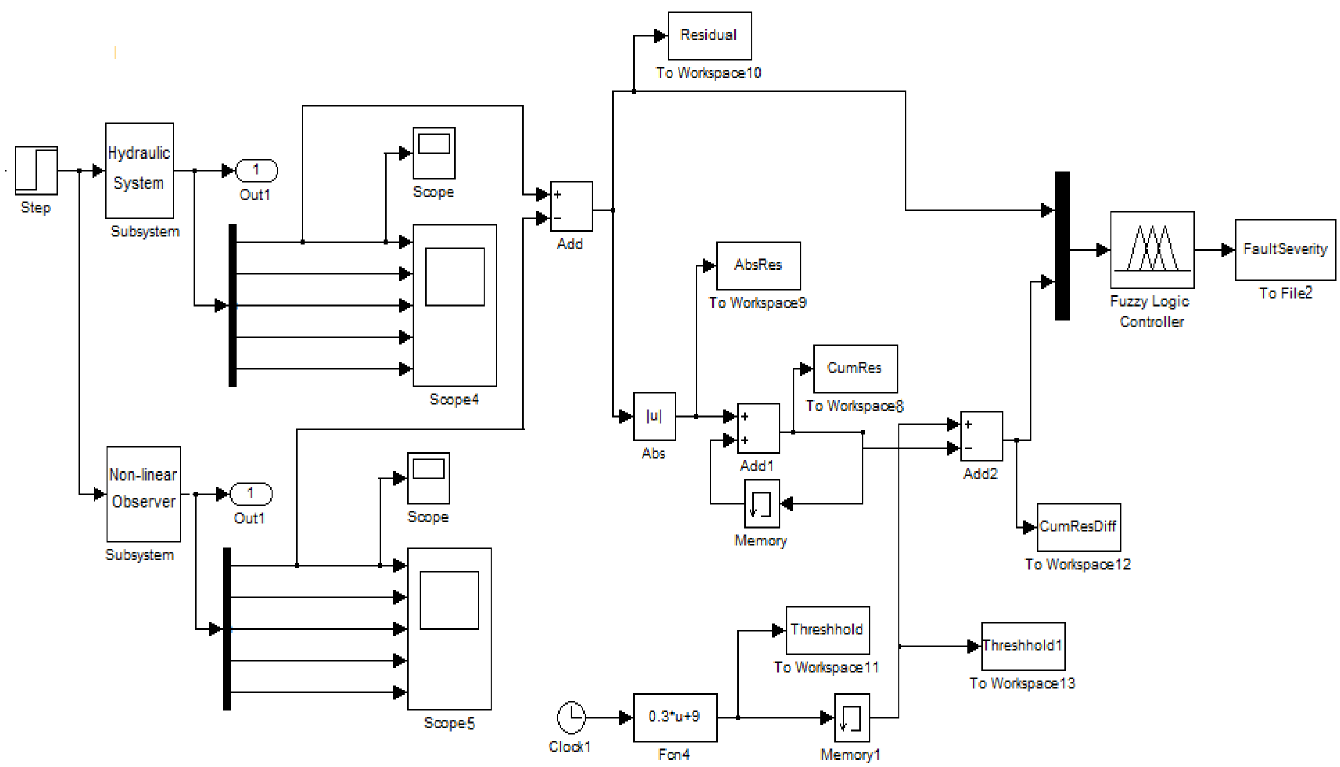

Fig 10. MATLAB/SIMULINK mode

V. Simulation

This simulation was carried out in MATLAB SIMULINK using fuzzy logic controller from the fuzzy logic toolbox as shown in fig. 10. 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 the technicians 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.

Using fuzzy logic over conventional method like Wald's sequential test [4] has several advantages. It provides the important information about system's health in between the thresholds too. It provides information about smooth transition from no fault to faulty condition. This also helps in avoiding false triggers and missing alarms. Fuzzy logic is a good option because there is no general mathematical model available which describes the output fault severity based on the available inputs. The observed knowledge is directly used for fault detection process instead of any detailed modeling.

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.

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