Fuzzy Diagnostics System for Fault Detection in an Experimental Control Loop

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Abstract

This paper describes a Fuzzy System to be used in an experimental loop Fault Detection System. The experimental loop was built in the Nuclear Engineering Department of the University of Tennessee and consists of a level water control system, with flow, pressure, temperature, and level sensors. The system depends strongly on the pre-determined limit difference between the actual and predicted values (residual) that can be more or less tolerant. To overcome this problem a Fuzzy System was developed for improving the existing experimental loop fault detection system. The Fuzzy System was developed using the Matlab Fuzzy Logic Toolbox. Many situations were simulated, including those where the residuals are near the pre-determined limit, and the results were excellent, since the fault detection system detected the faults giving an additional parameter measuring the possibility of the fault occurrence, and thus better representing the real situations.

Introduction

The current fault detection system continuously monitors the data and compares them with values estimated from a data-driven model. Any significant mismatch between the actual sensor measurement and its estimated value indicates a system anomaly. A rule-based expert system was developed in order to isolate the faulty component. The rule base was established from model-simulated data. The rules consist of if-then statements based on the characteristic behavior of each studied fault, where the actual variable values are continuously compared with model predicted values. The effectiveness of the method developed was demonstrated through simulation and by implementation to an experimental control loop. The actual system depends strongly on the pre-determined limit value. Therefore, the fault detection system has a different performance if the limit difference between the actual and model estimated values is 5% or 10%. Besides, if the limit value were 5% there would be cases when one or more of the residual is 4.9% and the fault will not be detected.

The objective of this work is to develop a **Fuzzy System** for improving the existing experimental loop fault detection system. The Fuzzy Logic is more flexible than the classical logic, and is based on natural language. The basic concept underlying the Fuzzy Logic is that of a linguistic variable, that is, a variable whose values are words rather than numbers. Although words are inherently less precise than numbers, their use is closer to human intuition. Furthermore, computing with words exploits the tolerance for imprecision and thereby lowers the cost of the solution. The fuzzy system was developed using the Matlab Fuzzy Logic Toolbox. Many situations were simulated, including those where the residuals are near the pre-determined limit, in order to compare the results using the Fuzzy Logic approach.

Low Pressure Experimental Water Loop

The experimental loop was built in the Nuclear Engineering Department of the University of Tennessee, and basically consists of a water level control system, with flow, pressure temperature and level sensors (Ferreira and Upadhyaya, 1999). The system model was developed in Matlab-Simulink environment and

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was used to acquire data at different operating conditions. A schematic of this control loop is shown in Figure 1. The actual experimental loop setup is being used for performing the same tests in a real system where noisy data and other technical problems are present.

The system has the following components:

1. Inlet water piping with:
   - A Worcester series 75 motor-operated valve (identified as Inlet MOV).
   - Rosemount mass flow meter model 3095 MV (a multivariate pressure transmitter).
   - An integral orifice device used as one of the 3095 MV inputs.
   - A resistance temperature detector (RTD) used as the second 3095 MV input. The water temperature is used for compensating the value of water density in the mass flow rate calculations.
   - A turbine-type water velocity meter. Using the water temperature from the RTD, a mass flow rate can be obtained from this device. This turbine is identified in this paper as Inlet Turbine Flow meter.
2. Bypass water-piping line with another Worcester series 75 motor-operated valve. This valve is used to simulate aging faults in the constant speed centrifugal pump. Changing its valve position, thus changing the bypass flow, simulates pump discharge changes due to aging process.
3. Water tank. The LPWL system has basically two controllers acting one at a time. One is the water level controller and the other the mass flow rate controller. For the water level controller, a Rosemount pressure transmitter model 3051 is installed at the bottom of the water tank. The water column pressure in the tank is linearly proportional to the water height.
4. Outlet water piping line with the following devices.
   - An MOV is used to simulate either obstruction in the outlet piping due to material deposits or a fault in the MOV itself.
   - A turbine-type water velocity meter, which is identified as Outlet Turbine Flow meter.
5. Water reservoir with a water heater element. This heater element is used to keep the loop water at a constant temperature. This temperature is around 110 °F. If no heat is provided, the pump heat will increase the loop water temperature up to 95 °F during a 6 to 7 hours of loop operation.

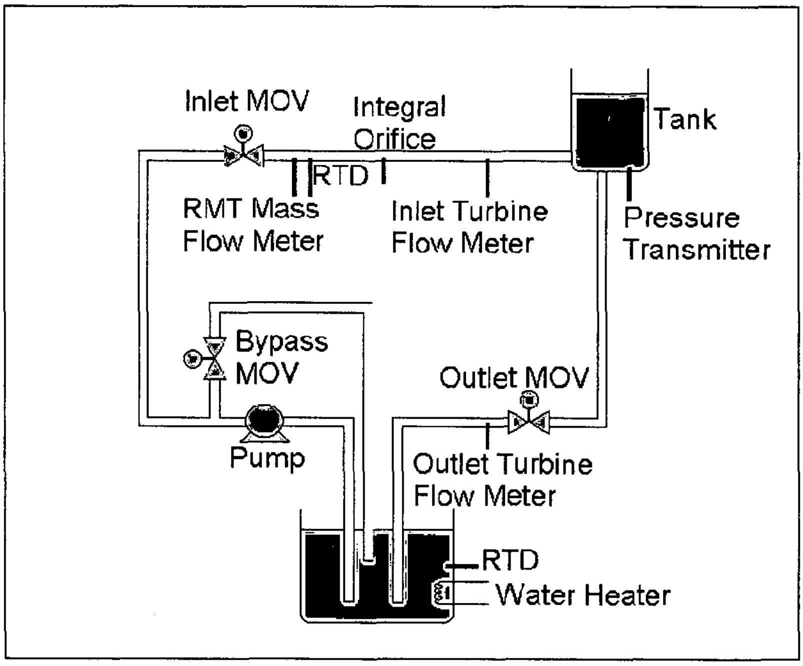

Figure 1. A schematic of the low-pressure water loop.

Actual Fault Detection System

A Fault Detection System was developed for the experimental loop described above. Basically this system continuously monitors the data and compares the actual values with those estimated from a data-driven model. The residual is the difference between a loop variable (such as a temperature sensor) measurement and its model predicted (analytical) value. In a normal system operational condition, each individual residual should be close to zero, indicating a good agreement between the system-predicted condition and the actual condition. Normally threshold limits are used to delimit the region in which the residuals are considered satisfactory. If any residual goes beyond the threshold limits, it indicates a probability of a system anomaly (fault detection).

If a fault has been detected, the second step of Fault Detection System is activated, in order to isolate the faulty component. Normally, many system variables are influenced by the faulty system component. This makes it difficult to know which component is the cause and which one is the consequence. In this step, the Fault Detection System algorithm isolates the faulty component through an expert rule-based system. This expert system is based on the particular characteristics of each individual fault. A faulty component disturbs the system behavior in different ways not only for different types of sensors, but also for the same types of sensors that are in different system locations. Computer simulations using Matlab-Simulink model generated the rules of the expert system.

Fuzzy Logic Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns are discerned. The Fuzzy Logic Toolbox provides graphical user interface (GUI) for building, editing, and observing systems. To use the Fuzzy Logic Toolbox it is necessary to define the following:

- Input variable membership functions
- Output variable membership functions
- If-then rules
- Fuzzy logic operators and defuzzification method

Input Variable Modeling

The input variables are the difference between the actual and the predicted variable values (residuals).

1. Inlet flow
2. Outlet flow
3. Controller output signal
4. Water level
5. Water level set point
6. Outlet MOV valve position
7. Bypass MOV valve position

Figure 2 shows the membership function for the first input variable (input in1). The membership functions for the other 6 input variables are the same. The input variables are the difference between the actual and predicted variable values. The input variable labels are the linguistic variables: low, medium and high. Trapezoidal and triangle functions were used at first, because these are the simplest representations. The input variable range is 0 to 1, where the maximum value 1 corresponds to 10% of error between the actual and predicted values in the fault detection model. This 10% value is considered a high value, because this method is used for incipient fault detection.

Input variable: inlet flow (input in1)
Range: 0 to 1
Labels: low, medium and high

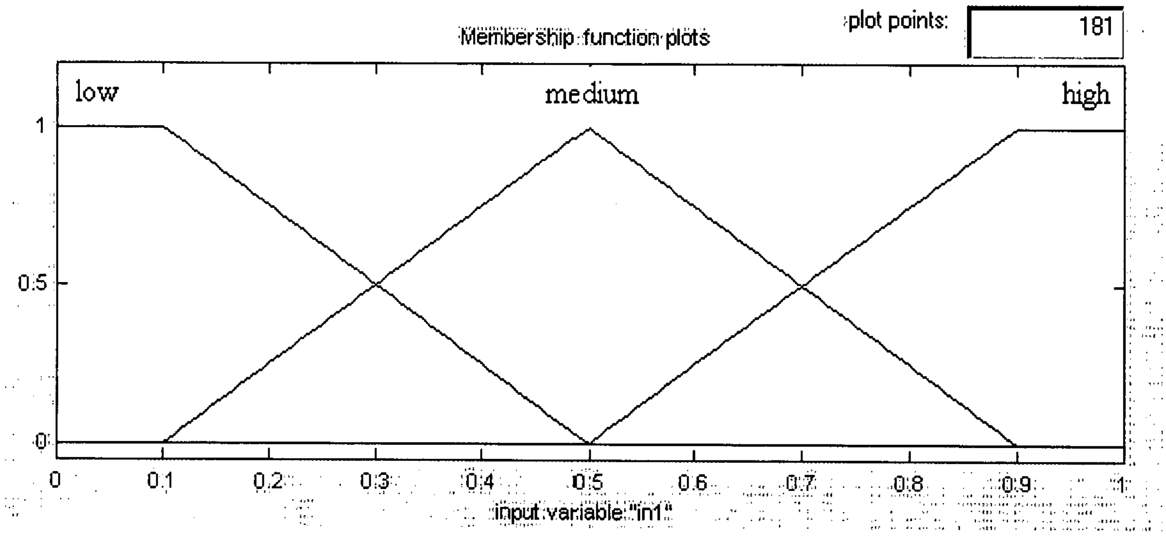

Figure 2. Input variable membership function.

Output Variable Modeling

The output variables are the 7 possible faults:

1. Water level sensor fault.
2. Outlet turbine flow meter fault.
3. Outlet MOV position device fault
4. Bypass MOV position fault.
5. Inlet MOV position device fault.
6. RMT flow meter fault.
7. Water level controller fault.

Figure 3 shows the membership function for the first output variable (fault 1 f1). The membership functions for the other 6 output variables are the same. The output variables are the possibilities of fault or no-fault. The labels are the linguistic variables *low* and *high*. The label medium was not included because the term medium probability of fault is not helpful for determining the fault criterion. Similar to the input variables, the output variable functions chosen are trapezoidal and triangular functions. The range is 0 to 1, where 0 corresponds to no fault and the 1 corresponds to 100% fault possibility.

Output variable: water level sensor fault (f1)
Range: 0 to 1
Labels: low and high

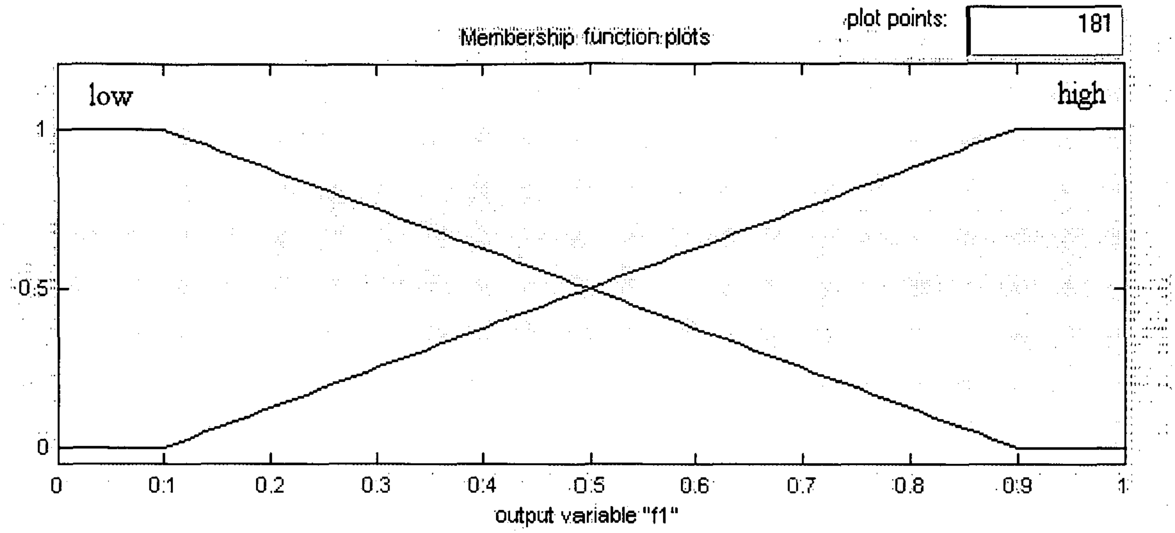

Figure 3. Output variable membership function.

Fuzzy System Rules

The present work is focused on improving the actual fault detection system in order to give the best performance in cases where the residual values are near the limit error value. Therefore, the rules of the new expert system will be the same as those of the existing one.

The expert system consists of a set of *if-then* rules. These rules were generated based on the experimental loop results where sensors and actuator faults were imposed. The rules for the 7 studied faults are:

1) IF (Inlet Flow rate Error > limit error)
   AND (Controller Output Error > limit error)
   AND (Bypass MOV Position Error < limit error)
   THEN Loop Faulty Component = Inlet MOV

2) IF (Outlet Flow rate Error > limit error)
   AND (Water Level Error > limit error)
   AND (Outlet MOV Position Error < limit error)
   THEN Loop Faulty Component = Water Level Sensor

3) IF (Inlet Flow rate Error > limit error)
   AND (Water Level Error > limit error)
   THEN Loop Faulty Component = Inlet Flow rate Sensor

4) IF (Outlet Flow rate Error > limit error)
   AND (Water Level Error > limit error)
   AND (Outlet MOV Position Error > limit error)
   THEN Loop Faulty Component = Outlet MOV

5) IF (Inlet Flow rate Error > limit error)
   AND (Controller Output Error > limit error)
   AND (Bypass MOV Position Error > limit error)
   THEN Loop Faulty Component = Bypass MOV

6) IF (Outlet Flow rate Error > limit error)
   AND (Controller Output Error > limit error)

THEN Loop Faulty Component = Outlet Flowmeter

7) IF (Water Level Set point Error > limit error)
   THEN Loop Faulty Component = Water Level Controller

Fuzzy System Operators and Defuzzification Method

The Fuzzy System described was implemented using the Matlab Fuzzy Logic toolbox. For the rules with two antecedents related with the connective *and*, the operator of intersection uses the *minimum* value. For each rule, the control action activation is calculated according to the antecedent combination. After finishing the inference, the control action aggregation uses the operator *maximum* from each rule contribution, generating a new function. The defuzzification method used is the *centroid* method that uses the area center of the inferred function. Figures 4 through 8 show the Fuzzy System developed.

Fuzzy System Results

Many simulations were run to verify the fuzzy system performance. Figures 9 through 11 show the simulation results for the following faults: inlet MOV fault (f1), inlet Flowmeter fault (f3), and Bypass MOV fault (f5), respectively. The fault possibility is related with the output variable values related to each other.

Figure 12 shows the results of a simulation where the input error was 4.9% (for a limit error of 5%). The fuzzy system detects the fault. This is an improvement in the actual system, because the actual system does not detect faults if the residual is below the limit value.

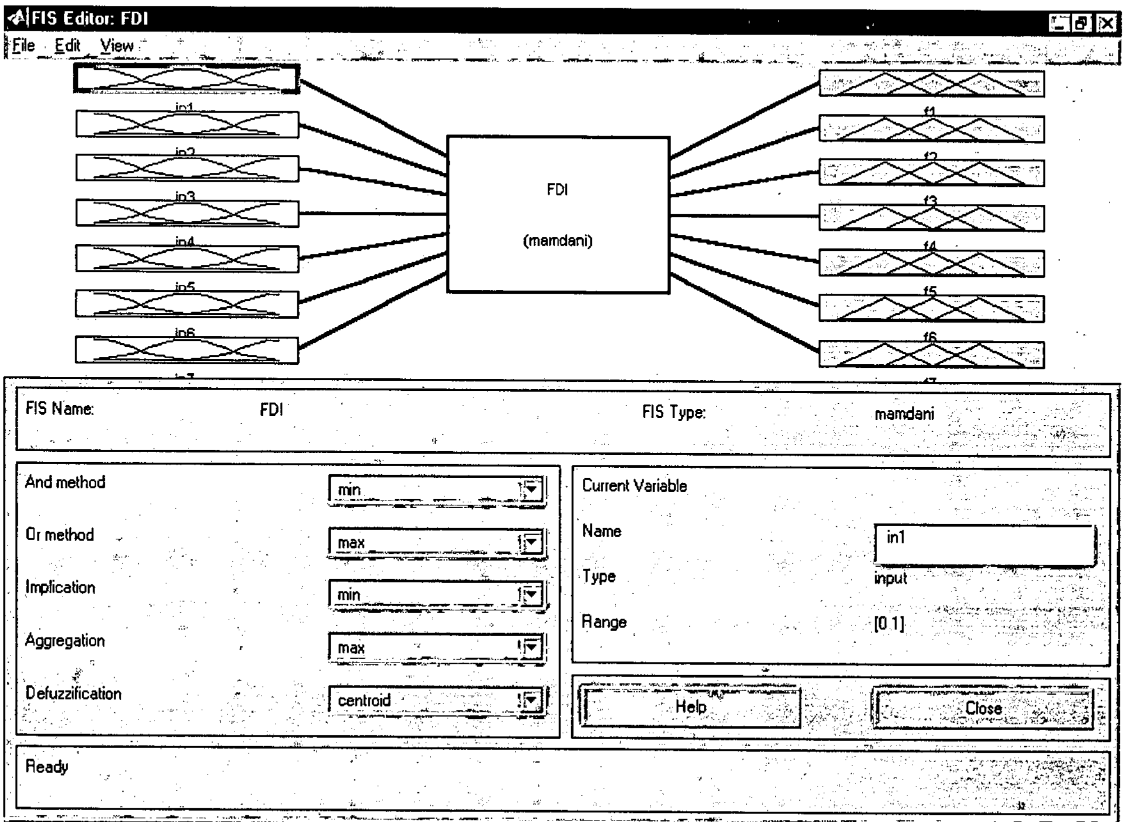

Figure 4. Matlab Fuzzy Logic toolbox main screen showing the input and output variables.

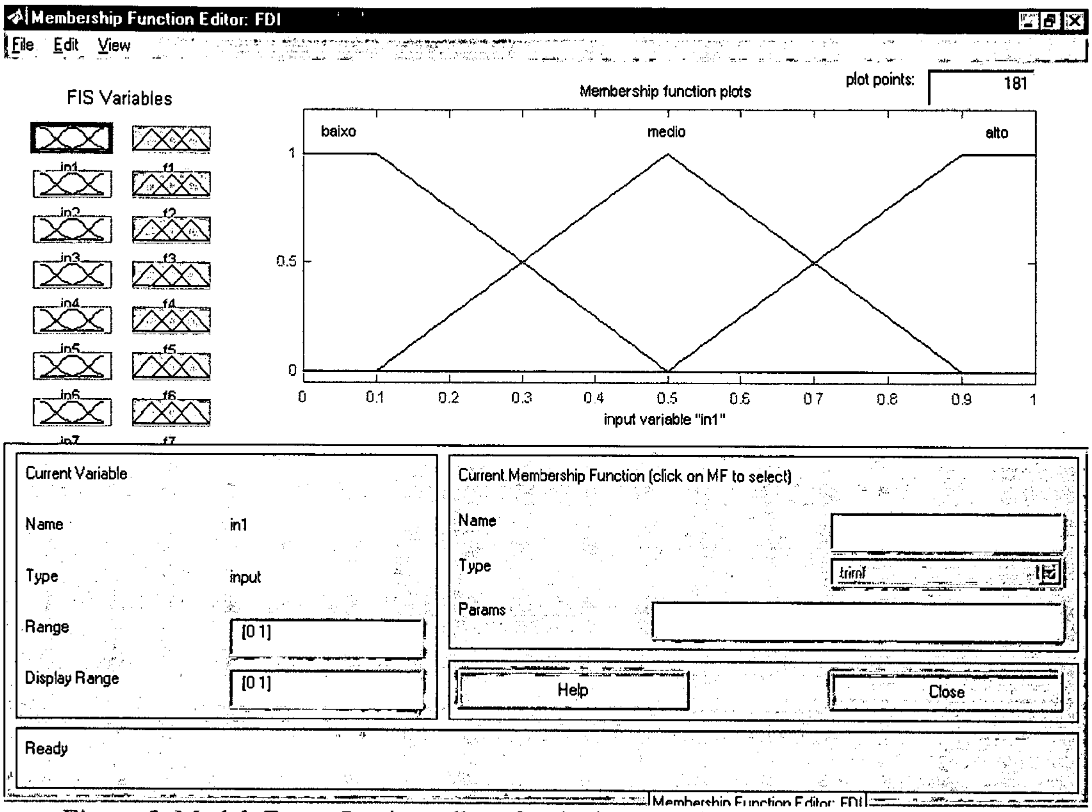

Figure 5. Matlab Fuzzy Logic toolbox for the input variable membership functions.

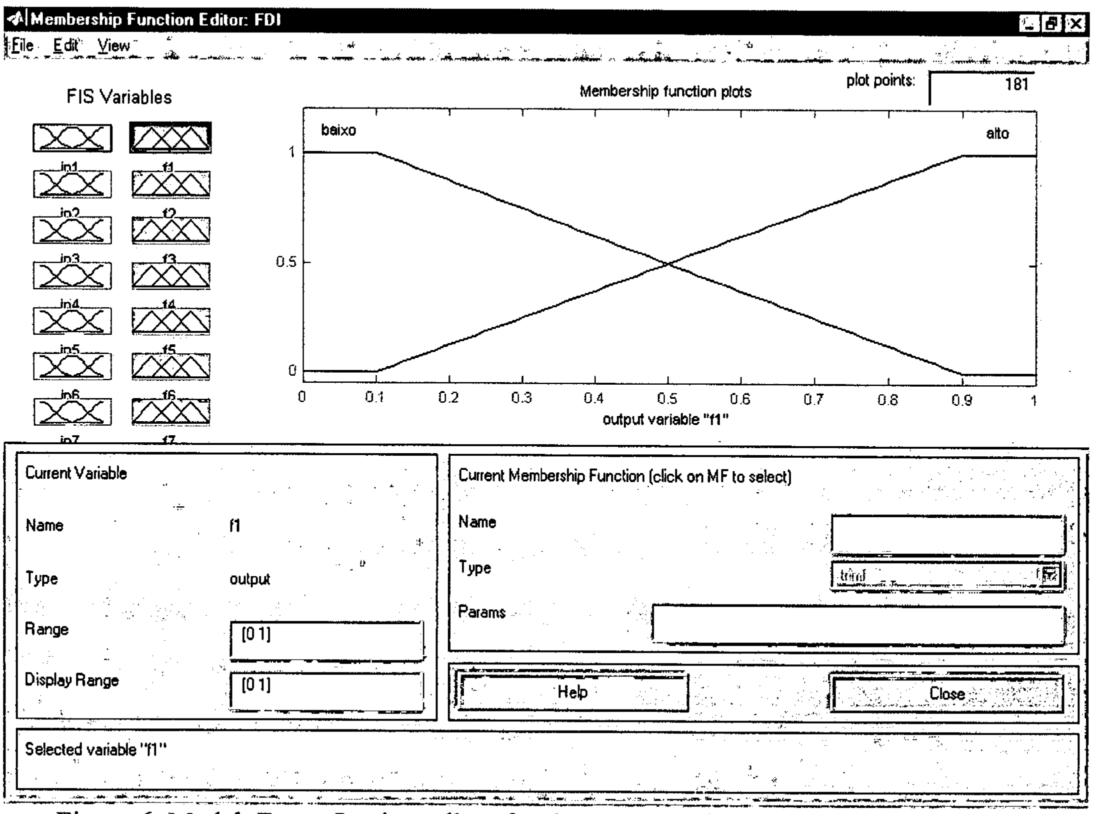

Figure 6. Matlab Fuzzy Logic toolbox for the output variable membership functions.

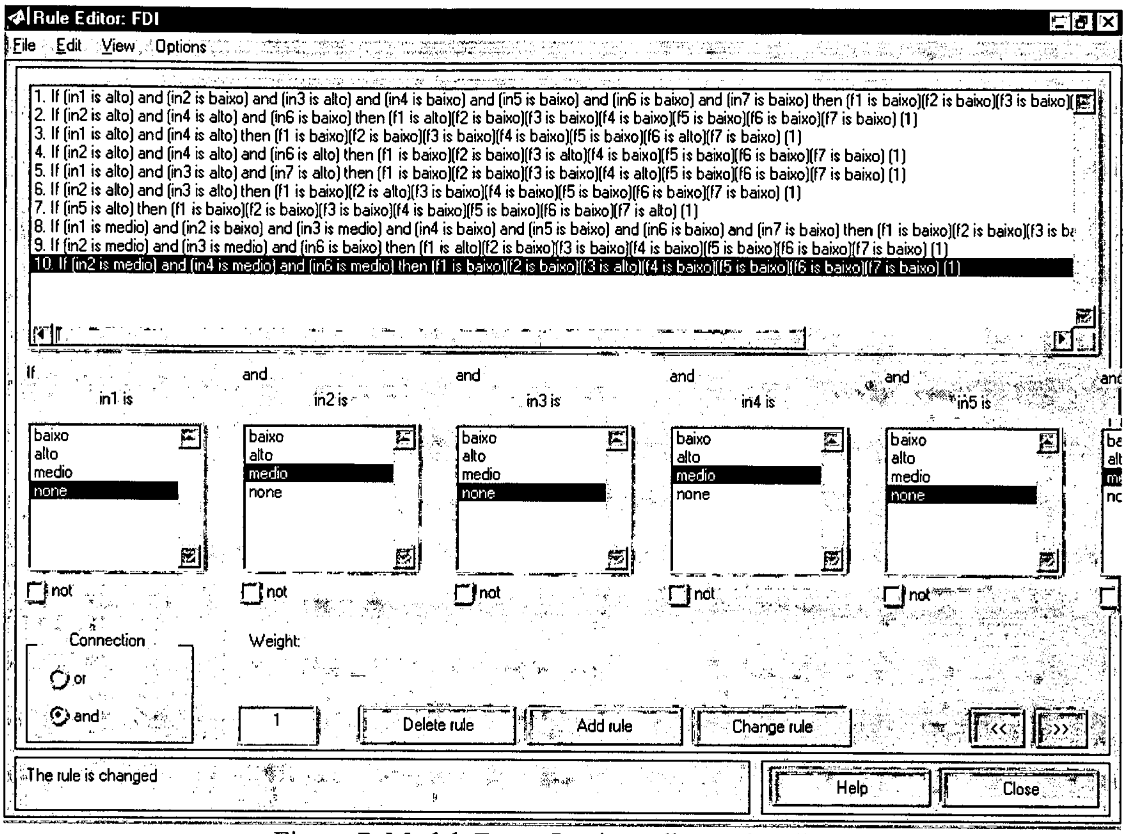

Figure 7. Matlab Fuzzy Logic toolbox rule editor.

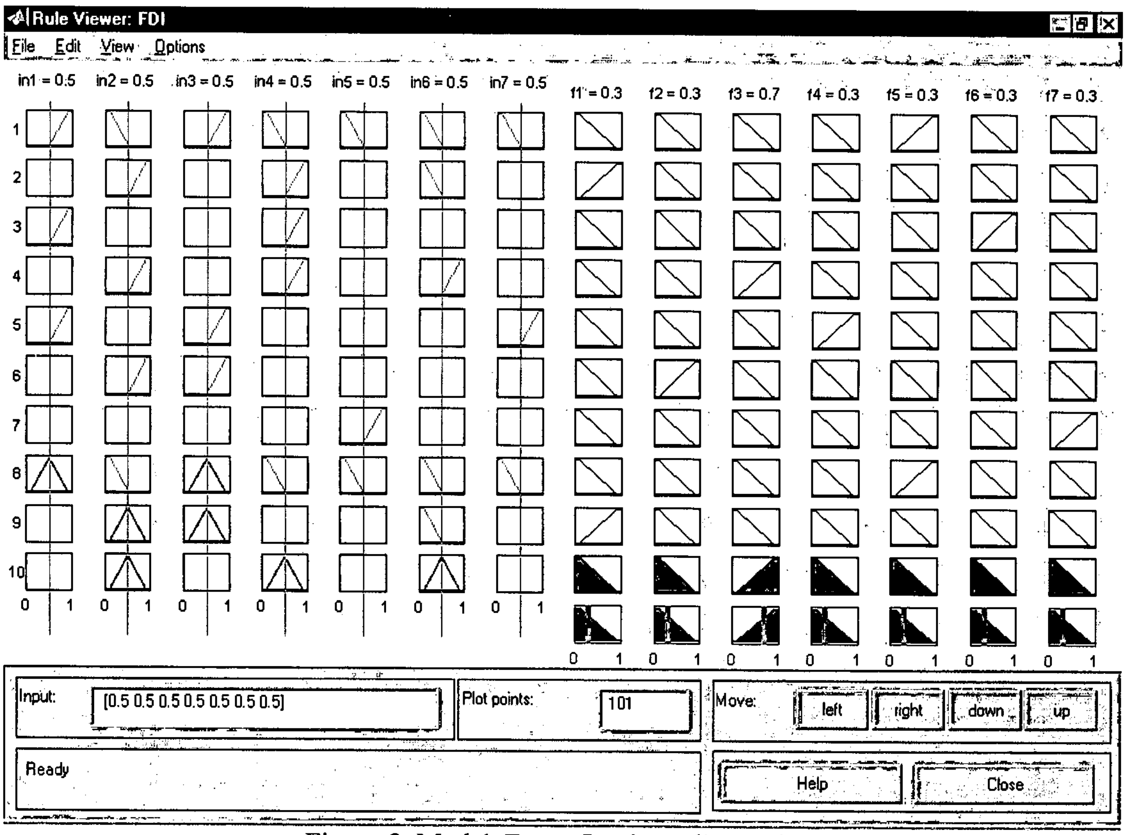

Figure 8. Matlab Fuzzy Logic toolbox rules.

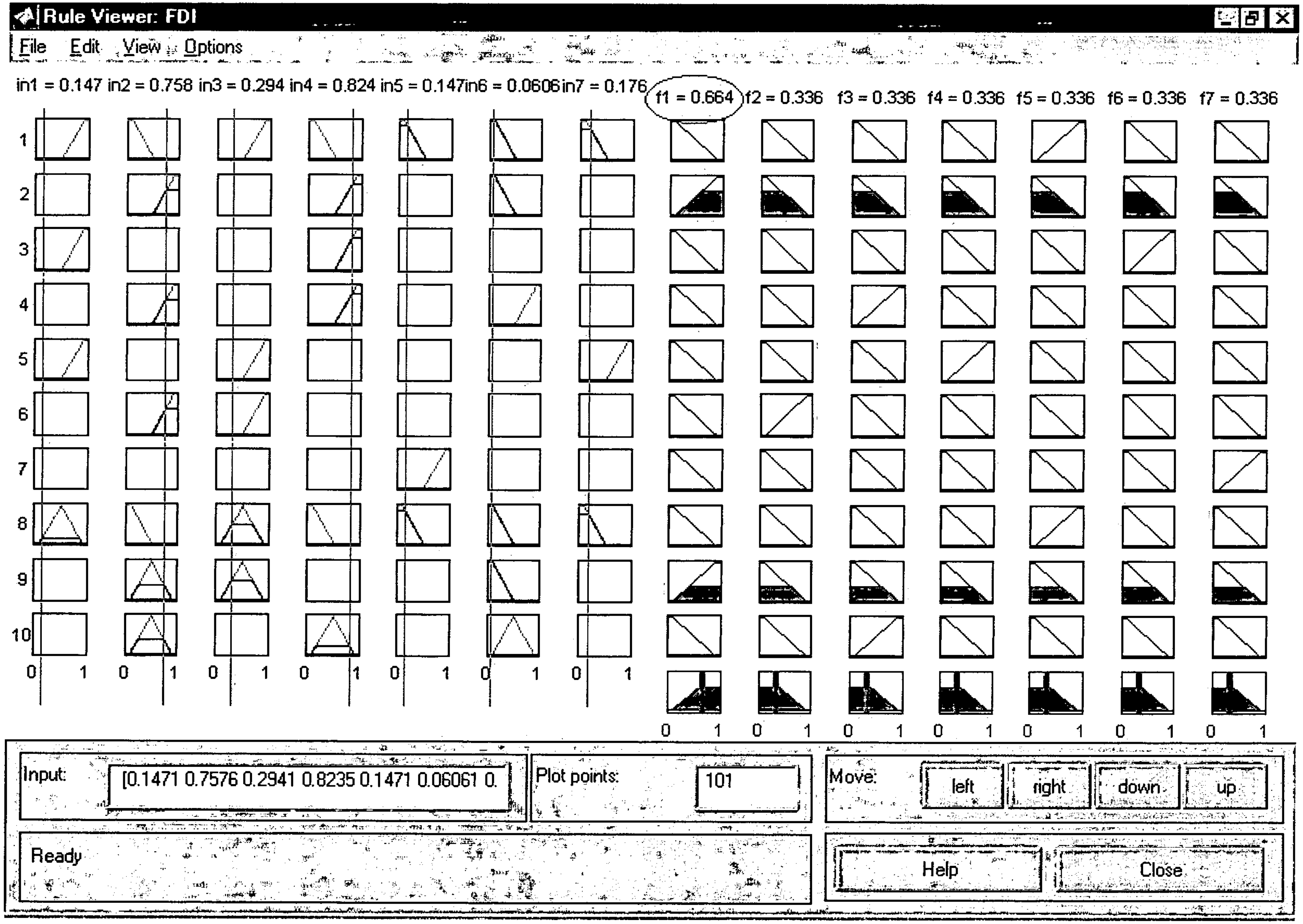

Figure 9. Result for the simulated fault f1: inlet MOV fault.

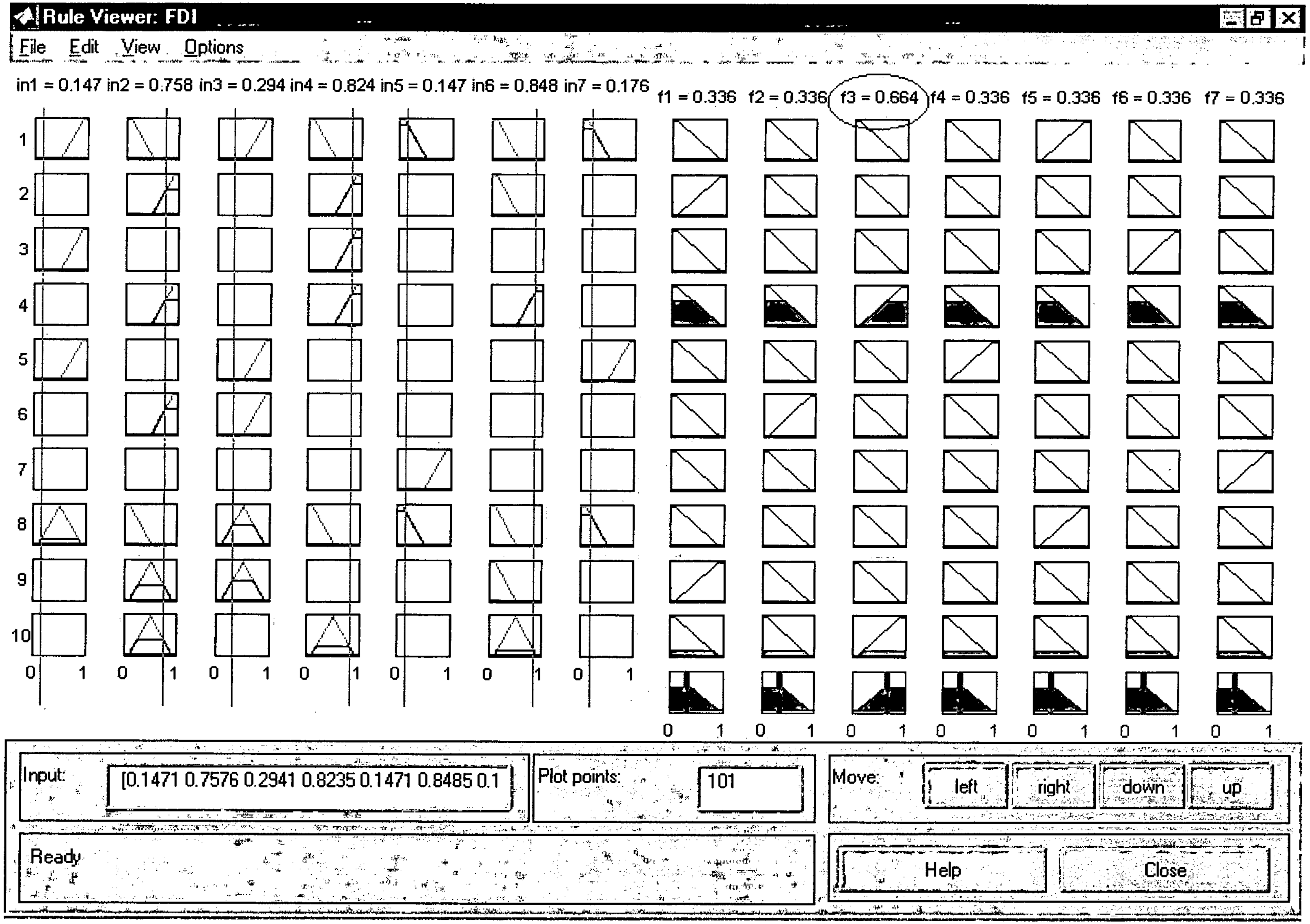

Figure 10. Result for the simulated fault f3: water level sensor fault.

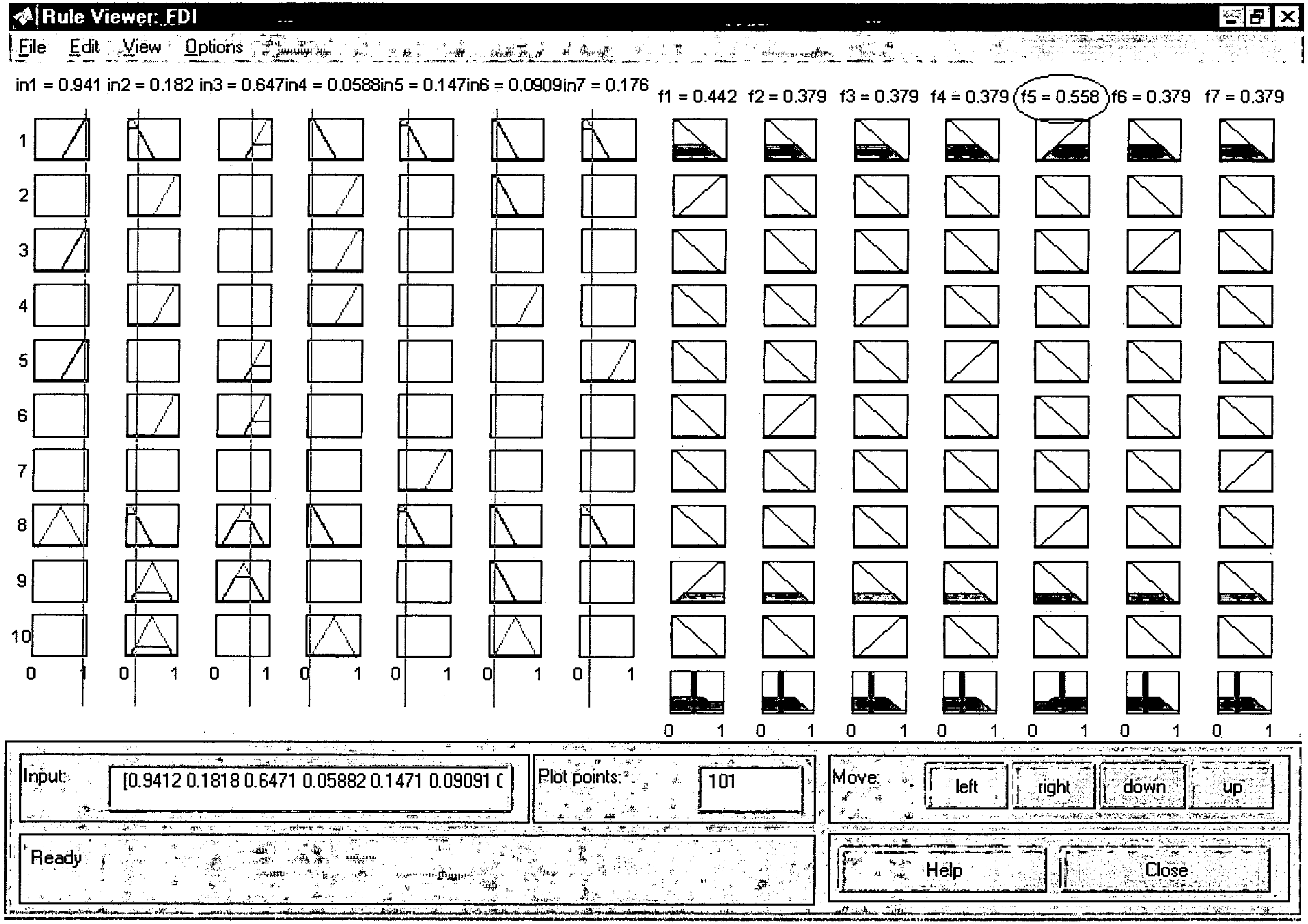

Figure 11. Result for the simulated fault f5: bypass MOV fault.

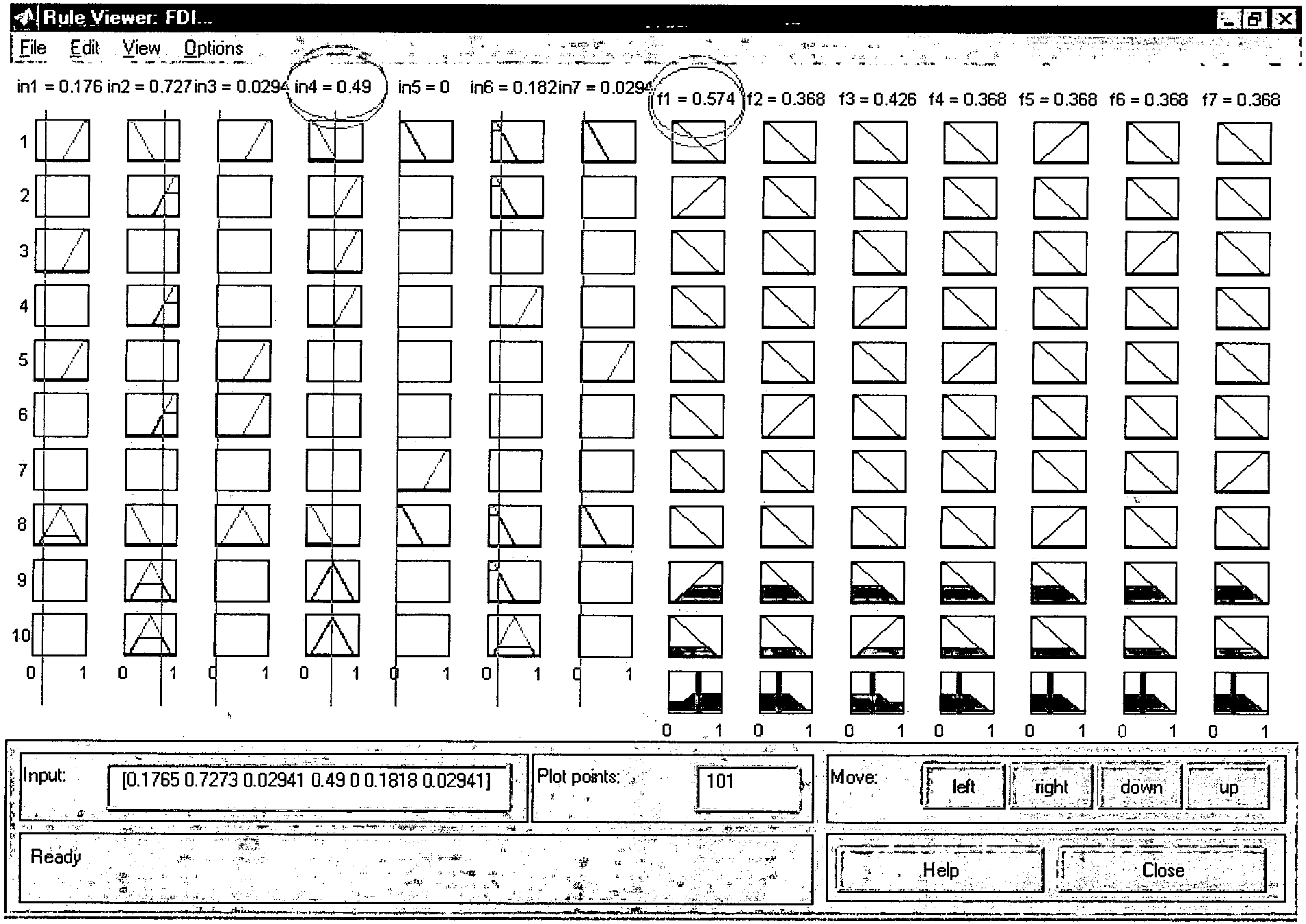

Figure 12. Result for the simulated fault f1: inlet MOV fault, where one of the input residual is 4,9%.

Conclusions

A Fuzzy System was developed for use in an experimental loop Fault Detection System. The experimental loop is instrumented with temperature and flow sensors and a control system that actuates a motor operated valve in order to control the water tank level at a pre-determined value. Different kinds of faults were studied for the experimental loop and the fault detection system does not detect the fault for cases where the error between the actual and predicted variable values is near but below a pre-determined limit value.

For the Fuzzy System implementation, the same rules developed in the conventional system were used. These rules were adapted for the Fuzzy System using linguistic labels for the variables instead of the exact values. The difference between actual and predicted variables is not compared with a limit value but they are classified into low, medium and high. In contrast with the output conventional system result that is *fault* or *no fault*, the Fuzzy System output shows a result with a fault possibility in a loop component. For the cases where the error is near but below the limit value, the Fuzzy System identified the fault.

References

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