



Fusion-Based Online Identification Technique for Pneumatic Actuator Faults

Bhagya R Navada* and Santhosh K Venkata*

Abstract

Pneumatic actuators are the most commonly used final control elements in industrial processes and abnormal behavior of which impacts the quality of the end product. Hence detection and identification of pneumatic actuator faults are essential. In most of the works, the time of detection of faults and the severity levels of the faults are not reported, and also the inflow to the control valve is not considered an influential parameter. In this work, an attempt is made to detect and diagnose two pneumatic actuator faults, a stem displacement fault, and an insufficient supply pressure fault using a decision fusion process. The two parameters such as valve stem displacement and the valve output flow rate are considered for the process of fusion. The decision fusion is performed using a fuzzy-based inference system to detect and identify the severity of faults into low, medium, and high faults. The experiment is conducted on a flow process and the proposed method can detect the faults online. The proposed technique can identify the insufficient supply pressure fault within 1-2s of its occurrence with a 100% detection ratio whereas stem displacement fault is detected within 3-6s of its occurrence with a detection ratio of 93.75%.

Keywords: Decision fusion; Estimation; Fuzzy logic; Fault; Flow process; Image.

Received: 6 July 2021; Revised: 22 August 2021; Accepted: 17 September 2021.

Article type: Research article.

1. Introduction

Process monitoring has become an essential requirement in many industrial processes in the present-day scenario. The monitoring system should be able to get all the information that is necessary to keep track of the required process parameters. A good measurement system leads to a good monitoring system. Employment of more sensors may lead to an increased overall cost and also the positioning of sensors would be a major concern. Thus to cope with the burden of cost, and to reduce the system complexity, soft sensors can be used. In most industrial processes, the flow process has become a prime component as there would be a requirement of maintaining the flow of raw materials and also end products based on the application. The flow rate is an essential parameter in many industries like oil and gas,^[1] iron and steel,^[2] chemical,^[3] food,^[4,5] seed flow,^[6] pharmaceutical,^[7] and dairy,^[8] etc. these industries also involve measurement and control of many other parameters.

Monitoring the components which influence the behavior

of the process to the maximum extent should be the highest priority. Sensors are devices that measure any quantity and are very essential in recognizing the behavior of any system^[9] Actuators are devices that convert the electrical signal into physical quantity. Sensors are important in measuring the required parameters in industrial processes whereas the actuators are necessary to impose the control action on the process. Sensors measure a physical quantity and represent them in electrical form whereas actuators convert the electrical signal into a physical quantity.^[10] The components which are in direct contact with the process are the final control elements. These elements convert the control signal into action in the process so any malfunctioning of these components would affect the process to a greater extent. The most commonly used final control element in the process industry is the pneumatic actuator. Pneumatic actuators are used in many industries to control the flow, level, temperature, and various other parameters of the fluids, gas, and slurry. To avoid unnecessary interruption as a consequence of process disturbances such as valve and other component failures, manufacturers have been using traditional operating conditions that result in the inefficient operation of the plant and increase overall production costs. Poor control performance is caused not only because of bad controller tuning but also due to undesired characteristics of control valves. Due to the occurrence of

Centre for Cyber-Physical System, Department of Instrumentation and Control Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India.

*E-mail: kbgabya@gmail.com (B. Navada), kv.santhu@gmail.com (S. Venkata)

faults in control valves the industrial plants schedule shutdowns to maintain the control valves. The control valves need to be repaired or replaced frequently due to the repetitive occurrence of faults, which add up to the overall maintenance costs. The chief factors that cause faults in the pneumatic actuators include air leakage, insufficient supply pressure, impurity in the air, blockage in the vent, and friction in the movement of the control valve. The ability to detect the occurrence of faults in the control valves will reduce downtime, increase product quality, and eliminate the avoidable replacement of functioning valve components.

There is a requirement for the benchmarking system when it is not possible to implement the developed algorithm in real systems. The majorly used benchmark system for pneumatic actuator fault detection is the Development and Application Methods for Actuator Diagnosis in Industrial Control Systems (DAMADICS) which was first reported to be utilized in fault diagnosis studies of the actuator in a sugar factory in Lublin, Poland. There are many faults associated with pneumatic actuators that are reported based on the DAMADICS benchmark system. There are a total of 19 faults associated with pneumatic actuators under the category of servomotor, control valve, positioner, and other faults. These actuator faults have been categorized into abrupt and incipient faults.^[11] Abrupt faults are fast-developing faults and incipient faults are the faults that exhibit changes slowly with time. Model-based methods are used for the pneumatic actuator fault detection using fuzzy models,^[12] adaptive neuro-fuzzy inference system.^[13] Karpenko *et al.*^[14] have detailed detection and identification of incorrect supply pressure faults, diaphragm leakage, and vent blockage fault using the neural network algorithm. In this case, time response parameters were used to identify the faults.

Data fusion is considered to be one of the reliable ways of fault detection methods. Data fusion is the process of combining the data from different/same sensor(s). The fusion can take place at the data level, feature level, or/and decision level. In this section, research in the area of data fusion for the detection and diagnosis of faults in different areas is highlighted. Diez *et al.*^[15] detailed the application of data fusion for the prognosis of industrial faults with the inclusion of machine learning techniques. Here the importance of data fusion in understanding the trend of normal and abnormal behavior has been briefed. Tidiri *et al.*^[16] highlighted a decision fusion strategy for the detection and diagnosis of fault using the Bayesian network. In this case, two detection algorithms one based on the model and the other on data have been considered. Based on the combination of these methods' output, a final decision was attained. This method has been applied to the Tennessee Eastman process for validation of the fault detection method. Tian *et al.*^[17] reported a fault diagnostic automatic system for the detection of machinery components faults. Here this method was subjected to a new class of faults that were not considered under training data. The feature fusion method is used for the detection of new faults and the

k-nearest neighbor technique was used classification of faults.

Fusion can be performed using many methods depending on the requirement of the application. Fuzzy logic is one of the methods for performing the decision fusion operation. Fuzzy logic is used in applications where there is no crisp differentiation of the data points. In this section, research in the area of data fusion for process monitoring based on fuzzy logic is discussed. Xuewei *et al.*^[18] have reported a data fusion-based fault diagnosis technique for transformer fault detection. A multi-band image sensor and a sensor for the detection of the discharge circuit are the two types of sensors used for the fusion process. A fuzzy model was created for fault and fuzzy-based data fusion was performed for the detection of transformer fault. Zhou *et al.*^[19] have proposed an information fusion technology for the monitoring of chemical enterprises. Information is collected from multiple sensors such as temperature, smoke, and dust concentrations and this information is fused based on the theory of fuzzy systems. Zhao *et al.*^[20] have reported the application of a data fusion algorithm in the cyber-physical system. The reported data fusion system was developed based on the Dempster-Shafer evidence theory and the fuzzy set theory. In this case, the fuzzy theory is used for determining the probability distribution of the evidence. Ge *et al.*^[21] have described a fuzzy decision fusion system for the process monitoring application. The process is monitored under different conditions to detect various process faults. The developed method was tested on the Tennessee Eastman benchmark system. Shrinivasan and Raol^[22] proposed a fusion technique for air-lane monitoring based on fuzzy logic. Fuzzy logic is used for the process of decision fusion with the data provided by multiple sensors. A type 2 fuzzy system was developed for making decisions in the presence of sensor uncertainties. Liu *et al.*^[23] reported a data fusion technique based on a fuzzy integral and fuzzy measure to diagnose the machinery faults. In this technique, fusion is performed at both the feature level and the decision level. Partial matching of different features was used with different degrees of matching. Multiple classifiers were used to categorize different machine faults as the first decision and then the fuzzy integral method was used for making the final decision. Majumder and Pratihari^[24] emphasized a multi-sensor data fusion technique based on fuzzy clustering to reduce the uncertain and imprecise data obtained from multiple sensors. Based on the similarity of the obtained data, they were clustered, and then the fuzzy predictive tool based on fuzzy reasoning was used to specify the output cluster. Sharman *et al.*^[25] explained a fuzzy adaptive data fusion system for the precision landing of the unmanned aerial vehicle. Kalman fusion algorithm is used for accurate state estimation to reduce the position error in the multi-rotor unmanned aerial vehicle landing. This method was developed to use in GPS-denied environments.

There are several faults associated with pneumatic actuators as specified by the benchmark system. For the detection of faults, observing many parameters would result in

an improved monitoring system. Data fusion is a technique that helps in combining data from many sources. Many techniques were used to perform the fusion of data and/or feature and/or decision. A fuzzy inference system is also used for performing the decision fusion for the detection of faults as mentioned before. Among the above-discussed research articles, they have used a fault model using fuzzy logic which is then used for the isolation of fault. In all aforementioned literature, the measurement of displacement was carried out using a contact type of sensor and the inflow to the control was not considered as a key influencing parameter.

The majority of the reported techniques for pneumatic actuator fault detection use fault detection systems with a single sensor, failure of such a sensor could lead to non-detection of fault. Sensor characteristics dominate the behavior of output on using a particular sensor, the user may have to compromise between sensor characteristics. A technique incorporating sensor fusion may overcome the above-said drawbacks and is prevalently a research gap.

- Many reported works concentrate on the detection of fault but the severity of fault is not discussed which is as important as finding the fault.
- It is important to locate the fault within a confined time based on the severity of the fault, which often varies with application. Most of the reported works have not discussed fault analysis in terms of time.
- Previous research^[12,13,15] reports the use of computational techniques mostly simulated and concentrated on classification. There exists a gap between implementation and simulation which needs to be overcome. The incorporation of intelligence/adaptation would yield a better system for real-life implementation.

In this work an attempt is made to measure the displacement using an image sensor and also the input flow rate is considered a supporting parameter for the detection of the fault. The proposed fault detection algorithm is also implemented on a real-life flow process.

This paper proposes a decision fusion system using fuzzy logic for the detection of insufficient supply pressure fault and stems displacement fault. The stem displacement of the control valve is measured using a camera mounted in front of the valve. The output flow rate of the valve is measured using an orifice flow meter and the input flow to the valve is measured using an electromagnetic flowmeter. Control valve stem movement is controlled based on the current-to-pressure (I/P) converter output that would be in the range of 3-15 psi. To obtain the full-scale movement of the valve stem, maintenance of the supply pressure above 15 psi is essential. Improper movement of the valve stem causing an abrupt change in output flow rate as a result of reduced supply pressure to the I/P converter is considered to be the insufficient supply pressure fault. Obstructed movement of the control valve even with sufficient supply pressure is considered to be the stem displacement fault which could be due to a jammed spring. The fault detection system collects data from the image sensor, inflow sensor, and outflow sensor, and fusion is performed using the fuzzy decision theory for the online detection and identification of stem displacement and insufficient supply pressure fault.

2. Experimental setup

A flow process station is considered for experimentation in this work. The experimental setup consists of a flow process with a reservoir, pump, rotameter, orifice meter, electromagnetic flow meter, and control valve. The water is pumped to flow through the electromagnetic flowmeter, control valve, rotameter, and orifice, and then back to the reservoir. The piping and instrumentation diagram of the experimental setup is depicted in Fig. 1 emphasizing the placement of the components in the setup. The dashed line indicates the water flow and the dotted line indicates the compressed air flow. A bypass valve is provided near the pump as a secondary path for the water to flow depending on the valve position. The orifice is connected with a differential

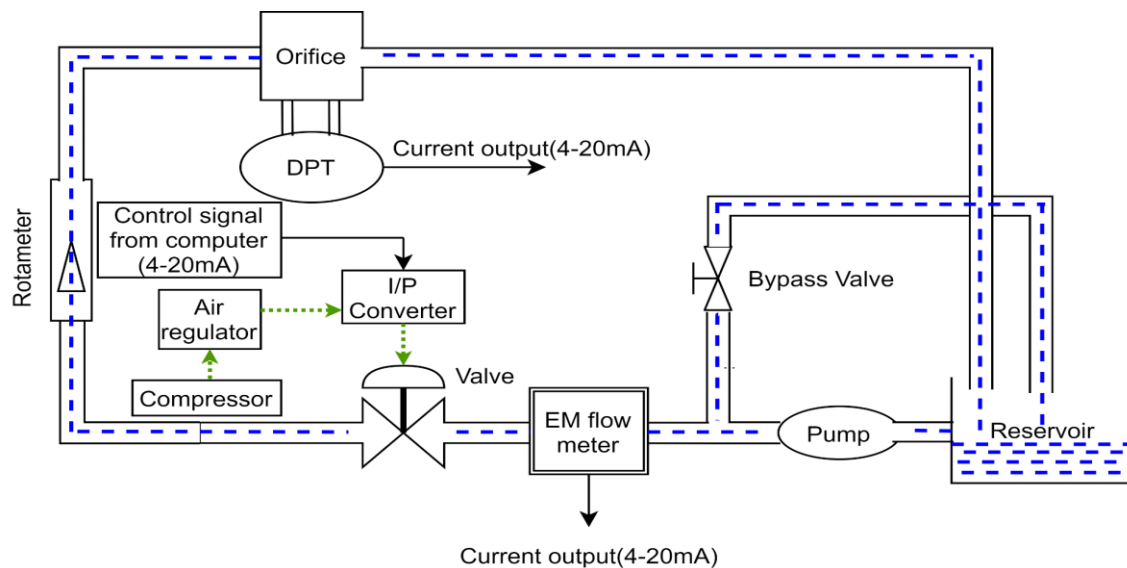


Fig. 1 Piping and Instrumentation diagram of the experimental setup.

pressure transmitter (DPT) for measuring flow rate and representing it as a current of 4-20 mA range. An image sensor is used for the measurement of the control valve stem displacement. An electromagnetic flowmeter is connected to the inlet of the control valve to measure the inflow rate and represent it as a current of 4-20 mA range.

The steps followed for the measurement of valve stem displacement using an image sensor are detailed in this section. The valve stem displacement is measured using the camera placed in front of the valve stem. The National Instrument (NI) Industrial Controller (IC) 3173 is connected to the computer through Ethernet and the camera is connected to IC 3173 using a USB 3.0 port. The camera captures the video and is acquired into the computer using the vision toolbox of LabVIEW software. The image processing steps and corresponding images for the valve stem displacement measurement are represented in Fig. 2. The acquired images are captured, converted to greyscale, and using the pattern matching function, the portion of the stem that is moving is considered to be the pattern to track. The total displacement of the valve stem between open and closed extremes is around 2.7 cm. The total scale area is considered the reference scale with which the stem pattern is compared in terms of pixel displacement using a caliper tool. The displacement in terms of the pixel is then converted into the displacement in cm.

The control input was given manually and then the actual displacement was measured manually with the help of a scale. The measured displacement of valve stem movement is then calibrated with multiple sets of measurements for increasing and decreasing control input with a step size of 1 mA. These measurements have been compared in Fig. 3 for the variation of control input from 4 to 20 mA and from 20 to 4 mA for 2 sets of inputs. From Fig. 3, it is noticed that both the sets of inputs are overlapping thus showing the repeatability of the readings. There is a maximum deviation at the peak due to the behavior of the control valve and manual measurement of valve stem displacement.

Once the valve stem displacement has been measured and

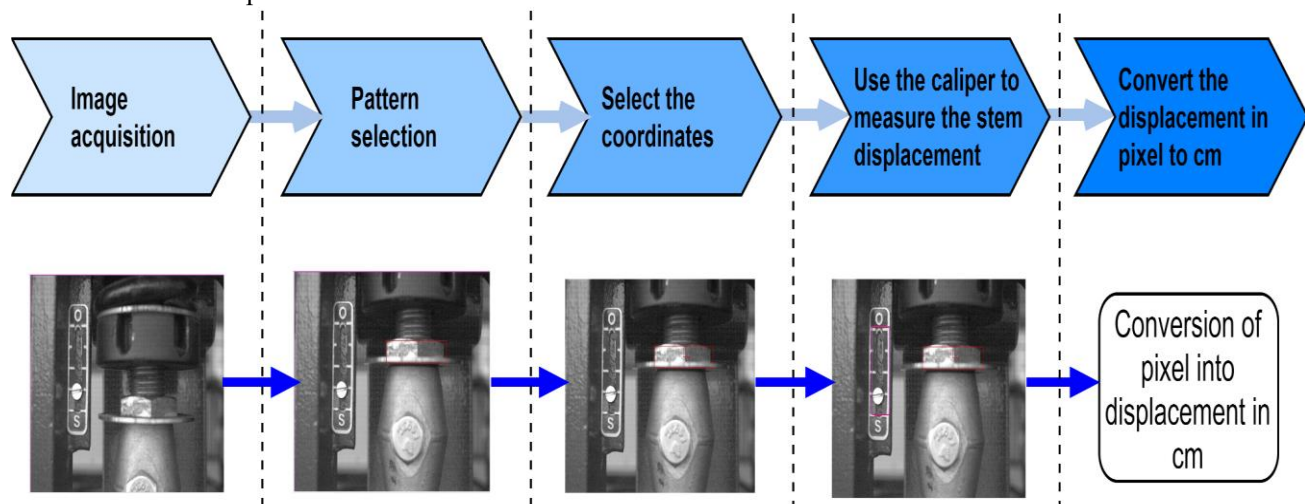


Fig. 2 Image processing step diagram for measurement of stem displacement.

converted into displacement in cm, the other variables have to be acquired for fault detection. The hardware connection diagram is represented in Fig. 4. The valve input and output flow rates are acquired through NI compact RIO (c-RIO) 9073 using the current input module (NI 9203). The c-RIO is connected to IC 3173 via the Power over Ethernet (PoE) slot with the selection of a suitable IP address. The data from c-RIO are collected by using a shared Public Subscribe Protocol (PSP) variable in the LabVIEW program as the c-RIO is not connected directly to the computer. Both image data and sensor data are acquired into the computer using NI IC 3173. A project is created in LabVIEW under which the Virtual Instruments (VIs) for measurement of flow rate and measurement of stem displacement are included. Then the project is built to run all the programs and use stem displacement as a global variable, all the variables are read in the main VI.

3. Methodology

In this work, a decision fusion system based on the fuzzy inferential fusion algorithm is proposed. The purpose of the fusion system is to detect two pneumatic actuator faults namely, insufficient supply pressure fault and stem displacement fault and identify the fault level as low, medium, and high. To perform the fusion, a framework is developed by considering Pau's data fusion framework as the reference. Pau's fusion framework is a sequential process of combining the data from multiple sources as symbolized in Fig. 5. This framework follows a hierarchical approach consisting of several basic stages that have to be completed before obtaining the overall output. Fusion is performed in sensor attribute and data analysis levels. A set of developmental rules are recognized to get the final representation of the fused output. Data is represented in a common format at the feature extraction level, and data association and decision-making are carried in the association fusion level and decision-making level respectively.^[26]

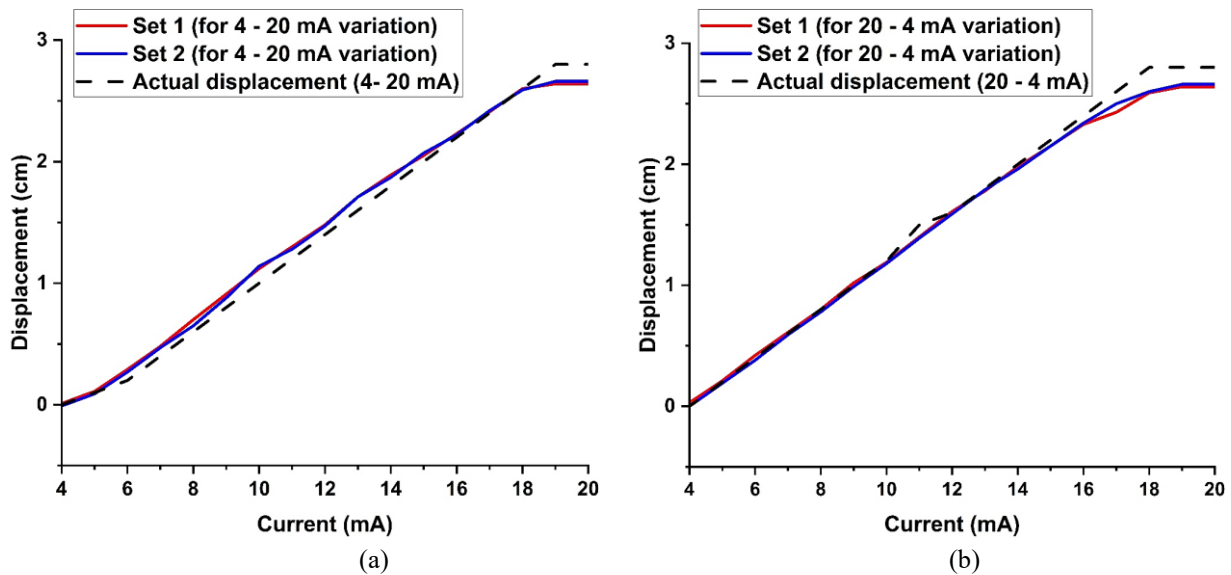


Fig. 3 Measured valve stem displacement for increasing and decreasing control input.

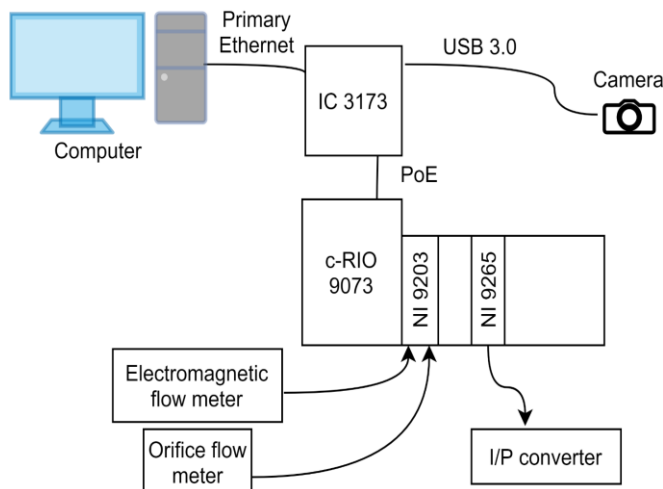


Fig. 4 Hardware connection diagram.

Model-based estimators are developed for the estimation of output flow rate, input flow rate, and valve stem displacement. The valve output flow rate is estimated using the transfer function $G1$ given in Eq. (1). The flow transfer function is identified by considering the control input to the I/P converter as the input parameter and the valve output flow rate as the output parameter. The valve input flow rate is estimated using an observer-based soft sensor developed using the transfer function $G2$ represented in Eq. (2). The stem displacement is estimated using the transfer function $G3$ given

in Eq. (3). The transfer function is obtained by considering control input as input and the stem displacement as the output.

$$G1 = \frac{27.73}{56s+1} e^{-4s} + 0.002 \tag{1}$$

$$G2 = \frac{0.615}{56s+1} e^{-10s} + 0.00159 \tag{2}$$

$$G3 = \frac{9990}{56s+1} e^{-4s} - 0.007 \tag{3}$$

An error signal (residue) is generated by subtracting the estimated value of the parameter from the actual value obtained from the respective transmitters. The error signal is collected for the normal behavior of the pneumatic actuator, and the minimum and maximum values of the error signals are calculated. Based on the calculated minimum and maximum values, the error signal is normalized to a range of 0 to 1 using a min-max normalization technique represented in Eq. (4). Thus, when the behavior of the sensor output deviates from its normal behavior, there will be a deviation in the normalized values in a positive or negative direction depending on the abnormality involved. The deviations above '1' and below '0' have been given equal weightage by converting the normalized error as given in Eq. (5). Here the value above '1' is considered as it is but the values below '0' are converted into a value above '1', thus giving equal significance for positive and negative variation in the error value as represented in Fig. 6. These normalized residues are given as input to the decision fusion system for the detection and identification of faults.

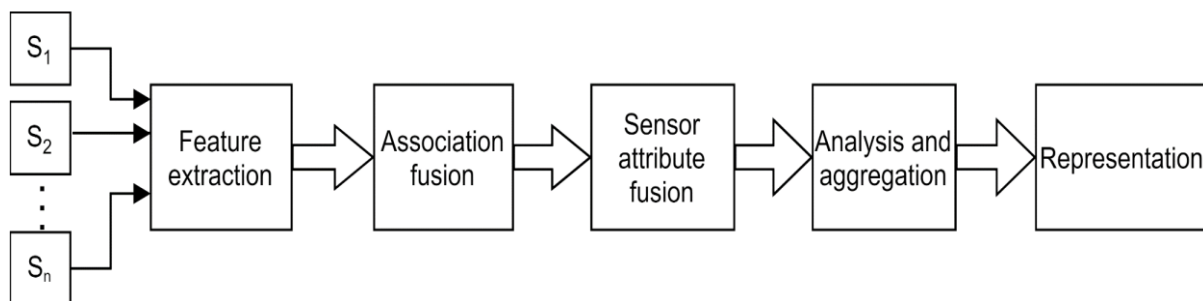


Fig. 5 Block diagram of Pau's framework.

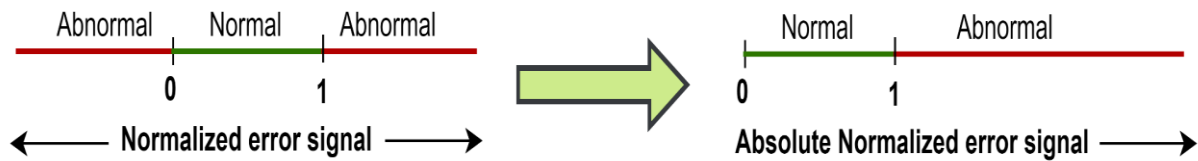


Fig. 6 Representation of error conversion.

$$e_{norm} = \frac{e - e_{min}}{e_{min_{max}}} \quad (4)$$

$$e_{n_abs} = \begin{cases} e_{norm} & \text{for } e_{norm} > 0 \\ |e_{norm} - 1| & \text{elsewhere} \end{cases} \quad (5)$$

where

- $e = x_{act} - x_{est}$ = error sample,
- x_{act} - the actual value of sensor data,
- x_{est} - the estimated value of sensor data,
- e_{min} - minimum of normal behavior error data,
- e_{max} - maximum of normal behavior error data,
- e_{norm} - normalized error sample,
- e_{n_abs} - absolute of normalized value.

The fusion of information obtained by multiple sensors is performed based on fuzzy theory for process monitoring applications.^[19] Decision fusion is a process of combining the soft decisions obtained by individual sensors or methods.^[21] In this work, two parameters such as valve stem displacement measured using an image sensor and the valve output flow rate measured using an orifice flow meter are considered. As the data collected were in different domains, a decision fusion method was considered to be the better way of performing fusion.^[27] A decision fusion system is developed using a fuzzy inferential fusion algorithm. Soft decisions are the relative decision from the sensors that are obtained from individual sensors employing which a final decision is obtained through a fuzzy-based decision fusion system.

The valve stem displacement and the valve output flow rate are the two significant parameters that emphasize the health of the pneumatic actuator.^[11] Thus, these two parameters are considered for the detection of pneumatic actuator faults. A flowchart of the fuzzy-based decision fusion process is depicted in Fig. 7. The proposed method includes the acquisition of data from the orifice, electromagnetic flowmeter, and image sensor. Model-based estimators are developed for the estimation of valve output flow rate, valve input flow rate, and valve stem displacement. The difference between the actual and the estimated values are the error signals which are used to detect any abnormalities in the pneumatic actuator.

Generally, in the process of decision-making, binary systems are used where ‘1’ represents the ‘yes’, and ‘0’ represents ‘no’. So in crisp logic, there are only two possibilities and there is no provision for the third possibility but in a real-life situation, there could be more possibilities other than these two. Hence to bring these real-life possibilities in the form of logic, fuzzy logic could be employed with infinite possibilities between ‘0’ and ‘1’.^[28] The proposed decision fusion process is represented in Fig. 7. The error data from each sensor are given as input to the fuzzy

inference system. The fuzzy inference system (FIS) consists of fuzzification, an inference engine, and a defuzzification process.

Fuzzification: The crisp normalized absolute values obtained from the sensors are given as input to the fuzzification process. Fuzzifier converts the crisp input values into a fuzzified output by creating various membership functions based on the range of values. In this process, one crisp value could be a member of more than one membership function with different membership values. In this application, the triangular and trapezoidal membership functions are utilized to create membership functions and are represented pictorially in Figs. 8(a) and 8(b), respectively. The belongingness of the variable value is represented as the membership degree ranging from 0 to 1.

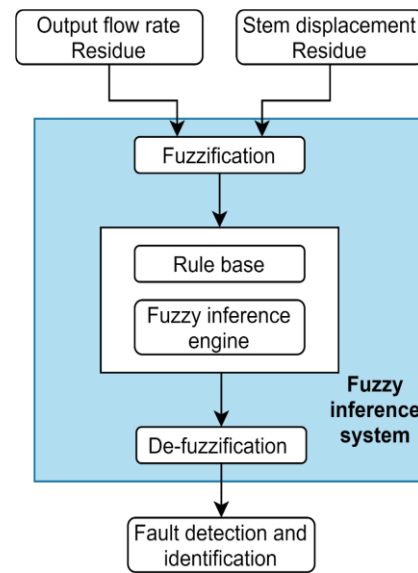


Fig. 7 Flowchart of the fuzzy decision fusion process

The triangular and trapezoidal membership functions are represented mathematically in Eq. (6) and Eq. (7), respectively.

$$\mu_A(x) = \begin{cases} 0 & \text{for } x < k \\ \frac{x-k}{l-k} & \text{for } k \leq x \leq l \\ \frac{m-x}{m-l} & \text{for } l \leq x \leq m \\ 0 & \text{for } x > m \end{cases} \quad (6)$$

$$\mu_A(x) = \begin{cases} 0 & \text{for } x < e \\ \frac{x-e}{f-e} & \text{for } e \leq x \leq f \\ 1 & \text{for } f \leq x \leq g \\ \frac{h-x}{h-g} & \text{for } g \leq x \leq h \\ 0 & \text{for } x > h \end{cases} \quad (7)$$

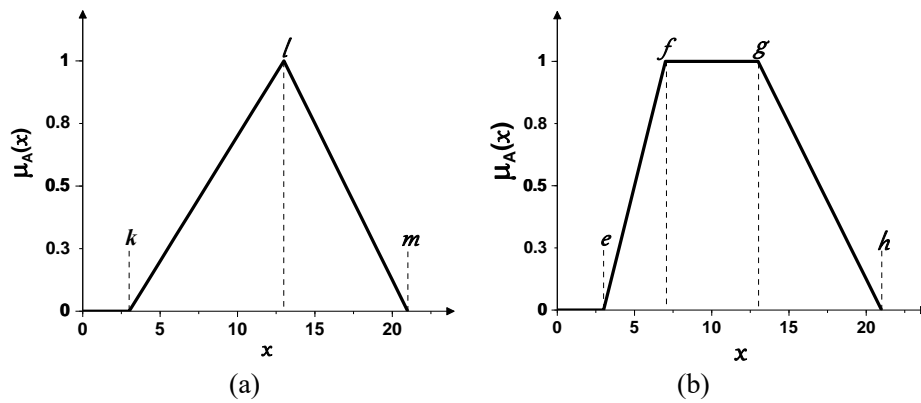


Fig. 8 Membership functions (a) triangular (b) trapezoidal.

Both the valve stem displacement and the valve output flow residues are converted into four membership functions namely, NORM, LOW, MED, and HIGH. The NORM membership function represents the range of values for normal behavior of the valve, and LOW, MED, and HIGH membership values represent the range of values for low, medium, and high-level fault respectively. Both NORM and HIGH being extreme membership functions, they are considered trapezoidal membership functions. LOW and MED membership functions are considered to be triangular membership functions.

Fuzzy inference engine: The process of mapping input fuzzy values to output fuzzy values through a fuzzy implication system is known as a fuzzy inference system. A rule base is developed with prior knowledge about the domain to obtain the required fuzzy decision outputs. Generally, the fuzzy rule can be defined in the form of ‘if p is X then q is Y’. In this rule, the part of the ‘if’ statement is called antecedent, and the part of the ‘then’ statement is called a consequent. The number of antecedents is not limited to one as it depends on the number of input variables.^[29] Creating a sufficient number of rules is necessary to get the required output fuzzy membership functions. In this work, the minimum antecedent implication (AND) method is used to join two decision outputs coming from individual sensors. Based on these individual decisions, rules have been generated to identify the fault as low, medium, and high severity fault. A total of 16 rules have been generated as represented in Table 1.

Table 1. Lookup table for decision fusion algorithm.

AND (min)		Stem displacement decision			
		NORM	LOW	MED	HIGH
Output flow decision	NORM	NORM	NORM	NORM	NORM
	LOW	NORM	LOW	LOW	LOW
	MED	NORM	LOW	MED	MED
	HIGH	NORM	LOW	MED	HIGH

The FIS for the diagnosis of insufficient supply pressure fault is represented in Fig. 9 which represents the membership functions created for output flow rate error, stem displacement error, and fault severity. The FIS for the diagnosis of stem displacement fault is represented in Fig. 10 which depicts the membership functions created for output flow rate error, stem displacement error, and fault severity.

The way the output fuzzy variable membership functions are considered is based on the type of implication used for the consequents. Here a minimum implication method is used to obtain the output membership function. For a particular combination of input variables, more than one rule could be executed, resulting in more than one fuzzy set. In such situations, the output membership functions are aggregated to obtain a single output fuzzy set, that is given as input to the process of defuzzification. In this work, a maximum aggregation operator is used which produces the sum of all the output membership values with their degree of support.

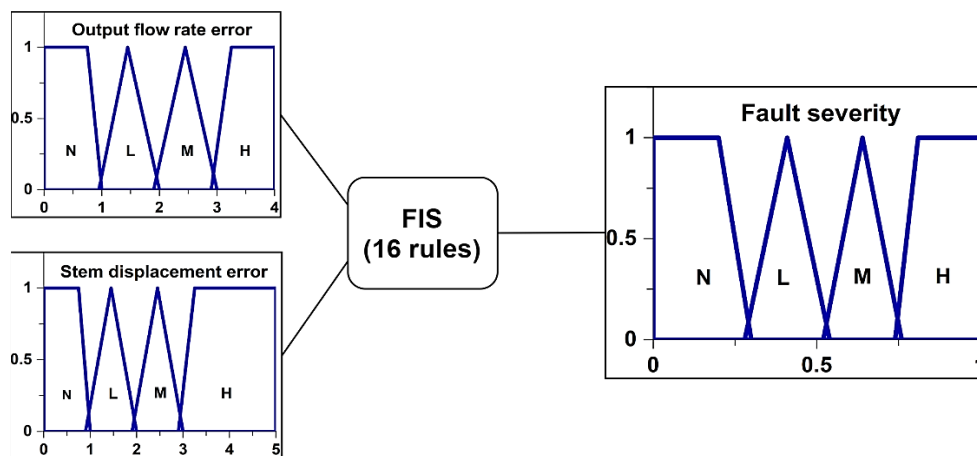


Fig. 9 FIS for the diagnosis of an insufficient supply pressure fault.

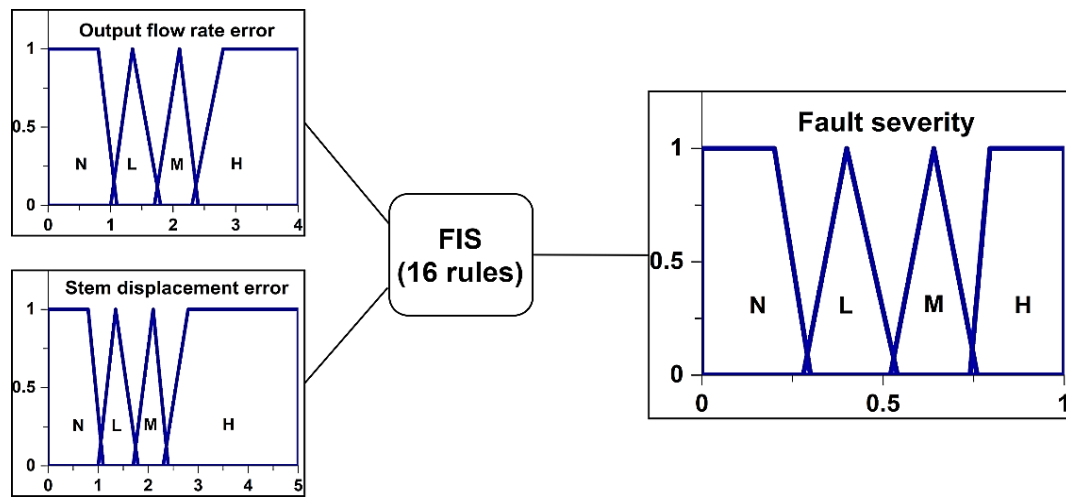


Fig. 10 FIS for the diagnosis of stem displacement fault.

Defuzzification: The process of converting the fuzzy output into a crisp output value is known as defuzzification. Once the process of aggregation is completed, the fuzzy outputs are converted into crisp values using the center of area defuzzification method. The center of the area is the method in which the center of the aggregated area will be considered as the defuzzified scalar value. The defuzzified value is obtained through the calculation represented in Eq. (8). The fuzzy system is developed on the LabVIEW platform with the help of the fuzzy logic toolbox.^[30] The defuzzified value between 0 and 1 represents the severity of the fault from normal behavior to a high fault.

$$Center\ of\ Area(Z_d) = \frac{\int_{Z_{min}}^{Z_{max}} \mu_A(z).z\ dz}{\int_{Z_{min}}^{Z_{max}} \mu_A(z)\ dz} \quad (8)$$

The type of connectives, implication, and aggregation methods used in this study has been represented in Table 2.

Table 2. Fuzzy methods are involved at different levels of decision fusion.

Fuzzy operators	Methods
Antecedent connective	Minimum (AND operator)
Fuzzy implication	Minimum
Aggregation	Maximum
Defuzzification	Center of area

4. Results and discussion

To check the working of the developed fuzzy decision fusion algorithm, the insufficient supply pressure fault is introduced by varying the supply pressure to the I/P converter using the air regulator at different levels with different fault durations. Here, the control signal is given by the user through the program using the current output module (NI 9265) connected to the c-RIO chassis. To observe the valve behavior for a varying control input, a sinusoidal control signal is given to the I/P converter as depicted in Fig. 11. Here the actual and estimated values of valve stem displacement are plotted in Fig. 11(a) and the corresponding fault index value is plotted in Fig. 11(b). The deviation of the actual value from the estimated

value wherever the abnormalities are involved has been highlighted in Fig. 11(a). The fault index value has two states ‘0’ representing the normal condition and ‘1’ representing the fault condition. Due to the behavior of the valve, we can observe a slight deviation at the peaks of the input for normal behavior. Under normal conditions, the actual value should have a minimum deviation from the estimated value. When there is abnormal behavior, it can be recognized by observing a large deviation of the actual value from the estimated value. Here only the abnormalities in the behavior of the pneumatic actuator have been tracked to indicate the fault and faultless conditions.

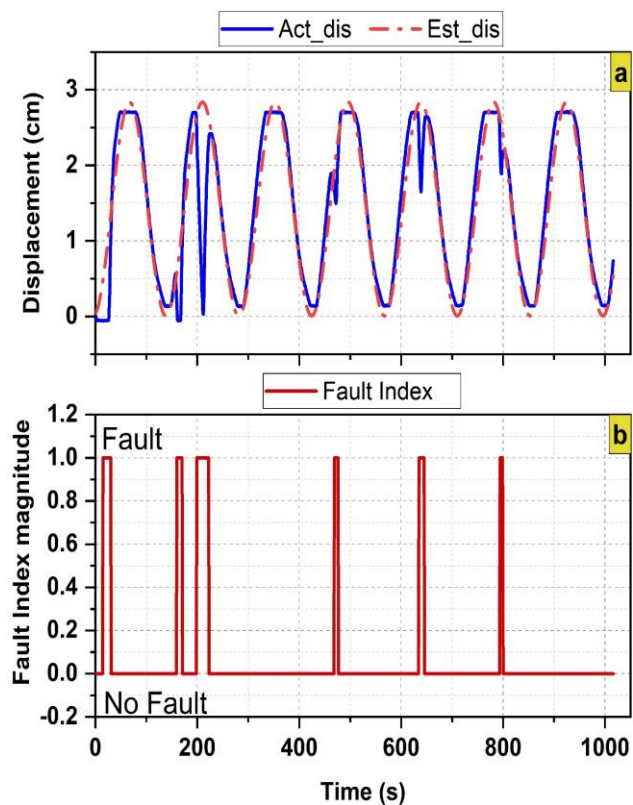


Fig. 11 Indication of the insufficient supply pressure fault (a) actual and estimated valve stem displacement, (b) fault index magnitude.

The actual and estimated values of the valve stem displacement and the fault index for insufficient supply pressure fault have been plotted in Fig. 12(a). To observe the time of fault detection, a part of the graph has been zoomed in and is represented in Fig. 12(b). A straight line has been drawn at the time of fault to observe the time of fault detection as illustrated in Fig. 12(b). From the graph, it is evident that the fault induced was able to detect within a second without any false alarms. The developed decision fusion algorithm is now subjected to a test for fault identification.

To minimize the false alarm rate, the minimum of the two inputs is considered so that only actual faults are identified.

The output flow rate deviates not only due to the change in stem displacement but also due to the change in the input flow rate. To identify the cause of change in the output flow rate, the input flow to the control valve is also considered. The actual and estimated values of valve stem displacement, valve output flow rate, and valve input flow rate have been represented in Fig. 13(a), Fig. 13(b), and Fig. 13(c) respectively and Fig. 13(d) represents the severity level for the insufficient supply pressure fault. From Fig. 13, it is observed that when the residue generated deviates from its normal values, depending on the deviation, severity output is generated. These severity levels are generated based on the

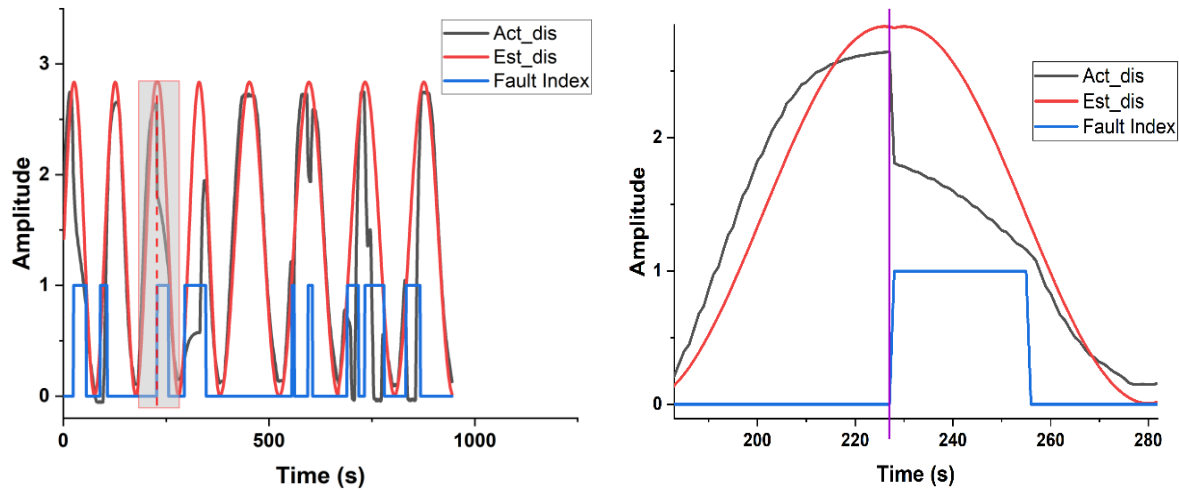


Fig. 12 (a) Representation of fault detection time for insufficient supply pressure fault (b) enlarged portion of the selected area.

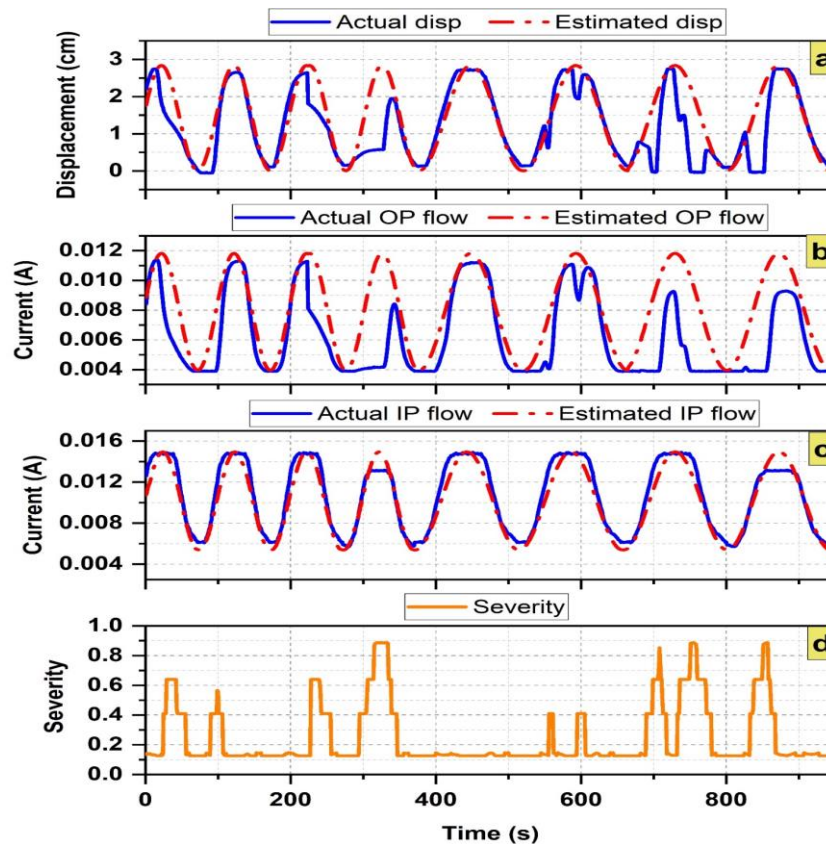


Fig. 13 Input and output response for insufficient supply pressure fault (a) actual and estimated displacement, (b) actual and estimated output flow rate, (c) actual and estimated input flow rate, (d) severity level of insufficient supply pressure fault.

fuzzy implication and aggregation process and are represented in Fig. 13(d). From the figure, it is observed that the deviation in the behavior of the pneumatic actuator is highlighted through the large difference in estimated and actual value.

The fuzzy fusion system was able to detect the insufficient supply pressure fault with low, medium, and high levels of severity. The introduced fault was able to detect within 1 to 2 sec of the occurrence of a fault. There was no false detection in the set of data with a high true detection rate. To check the working of the developed fuzzy decision fusion algorithm, the stem displacement fault is introduced by keeping an obstacle in the travel of the valve stem, thus hindering stem movement. A set of data collected for stem displacement fault and the corresponding fault indications have been represented in Fig. 14. The actual and estimated values of valve stem displacement are represented in Fig. 14(a) and the corresponding fault index magnitude is indicated in Fig. 14(b). Here only the abnormalities in the behavior of the pneumatic actuator have been tracked to indicate the fault and faultless conditions. As the threshold was a little high to reduce the false alarms, some very low faults were not able to detect as apparent in the graph.

The stem displacement actual and estimated values and the fault index for stem displacement fault have been plotted in Fig. 15(a). To observe the time of fault detection, a part of the graph has been zoomed in and is represented in Fig. 15(b). A straight line has been drawn at the time of fault to observe the time of fault detection as illustrated in Fig. 15(b). From the figure, it is apparent that the time taken for the detection of fault after the incidence of fault is 3 s for the data set considered.

The developed decision fusion algorithm is now subjected to a test for stem displacement fault identification. The output flow rate changes not only due to the change in stem displacement but also due to a change in the input flow rate. To identify the cause of the change in the output flow rate, the input flow to the control valve is also measured. The actual and estimated values of valve stem displacement, valve output flow rate, and valve input flow rate have been represented in Fig. 16(a), Fig. 16(b), and Fig. 16(c), respectively and Fig. 16(d) represents the severity level for the stem displacement

fault. From Fig. 16, it is observed that when the faults are induced, the residue generated deviates from its normal values, and depending on the deviation severity the output is generated. To minimize the false alarm rate, the minimum of the two inputs is considered so that only actual faults are identified.

The fuzzy fusion system was able to detect all the stem displacement fault levels: low, medium, and high levels of severity. The induced faults were able to detect within 4s on an average occurrence of a fault. But a very low-level fault around 440 s was not able to detect as the threshold selected was a little high. There was no false detection in the set of data with a high true detection rate.

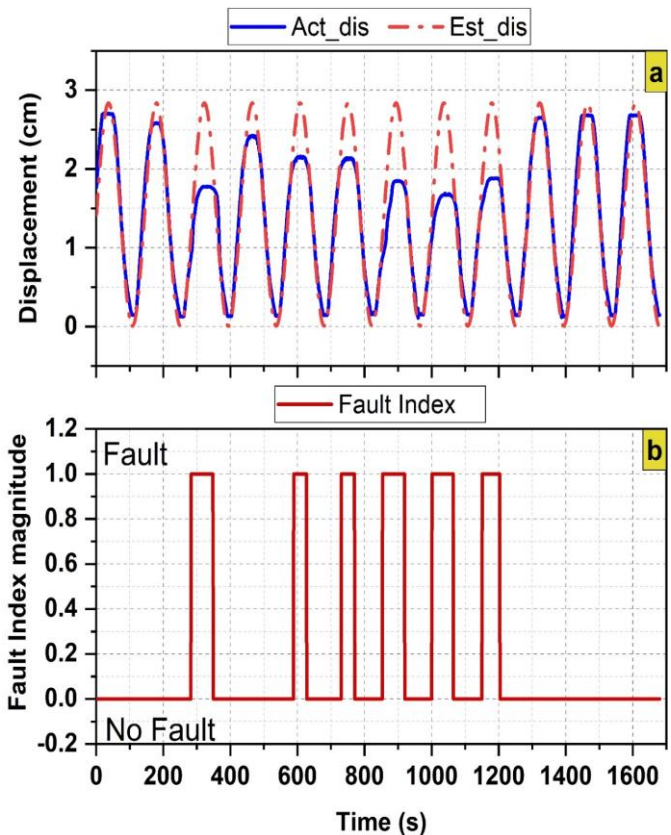


Fig. 14 Indication of stem displacement fault (a) actual and estimated valve stem displacement, (b) fault index magnitude.

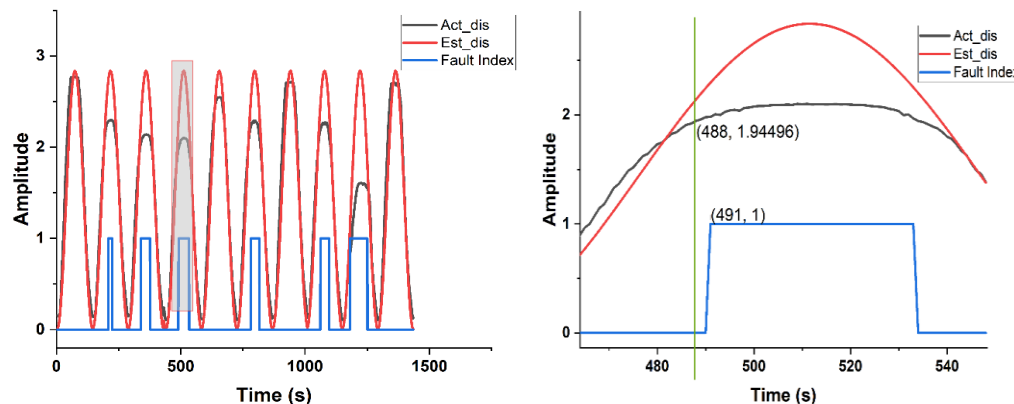


Fig. 15 (a) Representation of fault detection time for stem displacement fault (b) enlarged portion of the selected area.

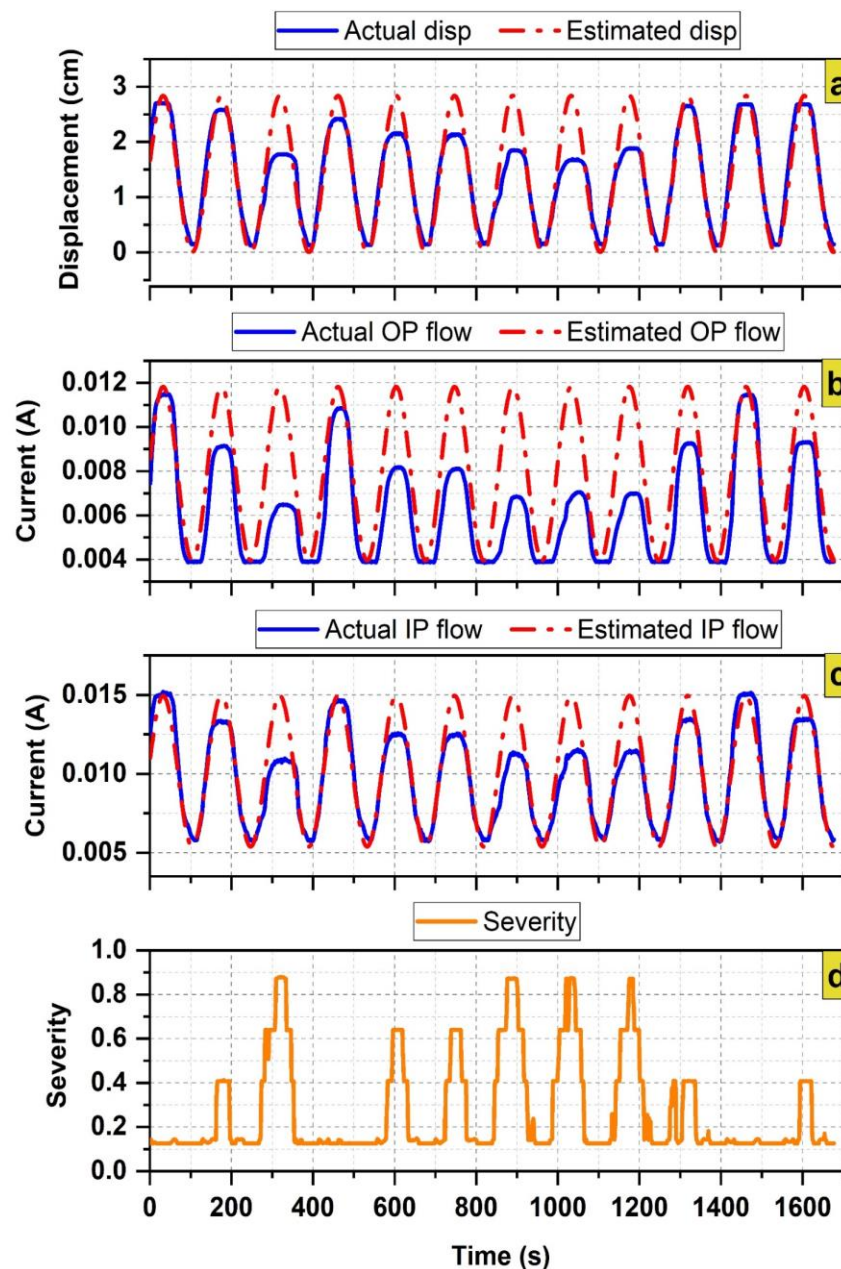


Fig. 16 Input and output response for stem displacement fault (a) actual and estimated displacement, (b) actual and estimated output flow rate, (c) actual and estimated input flow rate, (d) severity level of stem displacement fault.

The valve input low-rate residue was used to track the cause for the change in output flow rate whether it is due to the movement of the valve stem or due to a change in the inflow rate. The change in inflow rate during the normal behavior of the valve is utilized to notify the user about the valve inflow changes as represented in Fig. 17. The actual and estimated valves of valve stem displacement and valve input flow rate have been depicted in Fig. 17(a) and Fig. 17(b), respectively, and Fig. 17(c) denotes the corresponding valve inflow status. From Fig. 17(b) it is observed that the valve inflow rate changes with the valve stem displacement however, the abnormality involved in the valve inflow rate has been indicated in Fig. 17(c). The normalized error obtained by the inflow is adopted to notify the users about the abnormality at the valve inflow.

A comparison of the proposed method with some of the existing methods is tabulated in Table 3. From the table, it is evident that the other methods have detected the faults in offline mode whereas the proposed method was able to detect them in online mode. The time of fault detection was considered by Previdi & Parisini^[31] but the time of detection was high with a nominal detection ratio. The severity level was considered by Przystałka, and Moczulski^[32] and was represented as low, medium, and high levels. However, the low-level insufficient supply pressure fault was not able to identify and the medium level was identified with a very low detection ratio. From Table 3, it is significant that the inflow to the valve is not considered an influential parameter for the fault detection process.

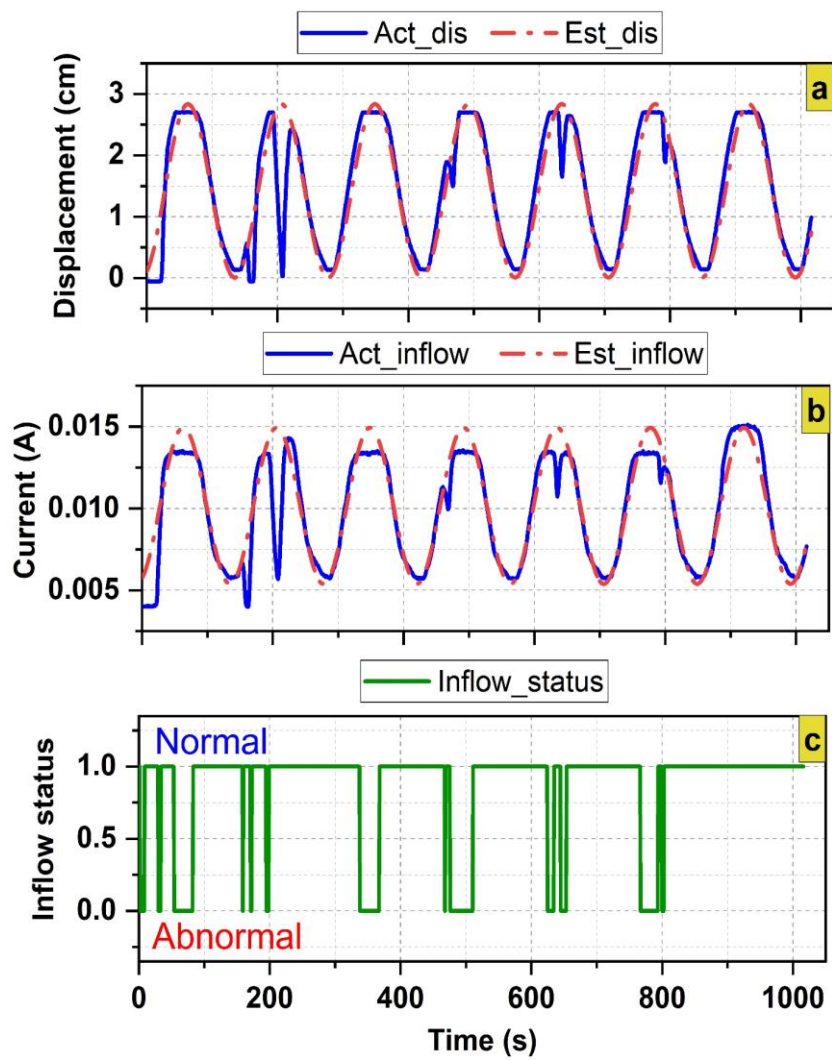


Fig. 17 Representation of inflow status (a) actual and estimated displacement, (b) actual and estimated input flow rate (c) inflow status indicator.

Table 3. Comparison of the proposed method with existing methods (ISP-Insufficient Supply Pressure fault, SD-stem displacement fault)

		Previdi & Parisini ^[31]	Przystałka, and Moczulski ^[32]	L. Ma <i>et al.</i> ^[33]	Proposed method
Method		Spectral estimation technique	Neural modeling using chaos engineering	Canonical variate analysis	Fuzzy-based decision fusion
Online fault diagnosis		No	No	No	Yes
Valve inflow indication		No	No	No	Yes
Fault detection ratio	ISP	-	99% (only for high-level fault)	53.74% (T2) 71.10% (SPE)	100%
	SD	83%	-	2.41% (T2) 0.00% (SPE)	93.5%
False indication	ISP	-	0%	4.11% (T2) 3.00% (SPE)	0%
	SD	2%	-	2.00% (T2) 0.67% (SPE)	0%
Fault detection time consideration		Yes	No	No	Yes
Fault severity indication		No	Yes	No	Yes

5. Conclusion

Process monitoring is an essential requirement in many industrial processes in the present-day scenario. As the actuators are the devices that are in direct contact with the process, any abnormality involved would influence the quality of the end product to a larger extent. In this work, the detection and identification of pneumatic actuator faults using a fuzzy-based decision fusion process have been addressed. Here the valve stem displacement and valve output flow rate are the two parameters considered for the process of fusion. Non-contact measurement of stem displacement is accomplished using an image sensor to isolate the sensor from the system vibrations. The valve stem displacement was measured using an image sensor with a root mean square error of 0.092 for dataset 1 and 0.08 for dataset 2 using the LabVIEW vision toolbox. Model-based estimators have also been developed for the measurement of valve output flow rate, valve input flow rate, and valve stem displacement variables.

Data fusion is considered to be one of the reliable ways of fault detection methods. As the data collected were in different domains, a decision fusion method was considered to be the better way of performing fusion. A fuzzy inference system was developed to perform the fusion of the two input variables. The final decision value ranges between '0' and '1' where values nearer to '0' represent the faultless condition and the values towards '1' represent the high fault condition. Insufficient supply pressure fault and stem displacement fault have been induced in the pneumatic actuator and were identified in online mode using a fuzzy decision fusion algorithm. The severity of the faults is categorized and indicated as low, medium, and high-level faults. The developed method was able to detect all the insufficient supply pressure faults with a 100% detection rate and zero false detection rate. The insufficient supply pressure fault was detected within a range of 1-2s after the incidence of the fault. The stem displacement fault was detected with a detection rate of 93.75% with 15 true detections out of 16 fault incidents. The stem displacement fault was detected around 3-6s after the incidence of the fault.

The valve output flow rate gets modified due to the stem displacement as well as the change in the valve input flow rate. Care has been taken in this work to differentiate among them. The inflow rate residue was employed to track the cause of the change in the output flow rate. This represents the cause for the change in the valve output flow rate whether it is due to a change in the valve stem displacement or due to a change in the valve inflow rate. The change in inflow rate under faultless behavior of the valve is used to notify the user about the inflow changes as depicted in Fig. 17. Isolation of insufficient supply pressure fault and stem displacement fault is the scope of work that we are still working on.

Conflict of interest

There are no conflicts to declare.

Supporting information

Not applicable.

References

- [1] P. J. LaNasa, E. L. Upp, Fluid flow measurement: a practical guide to accurate flow measurement, 1993.
- [2] J. Liu, R. An, R. Xiao, Y. Yang, G. Wang, Q. Wang, Implications from substance flow analysis, supply chain and supplier' risk evaluation in iron and steel industry in Mainland China, *Resources Policy*, 2017, **51**, 272-282, doi: 10.1016/j.resourpol.2017.01.002.
- [3] H. Xiao, D. McDonald, Y. Fan, P. B. Umbanhowar, J. M. Ottino, R. M. Lueptow, Controlling granular segregation using modulated flow, *Powder Technology*, 2017, **312**, 360-368, doi: 10.1016/j.powtec.2017.02.050.
- [4] P. M. B. Bugallo, A. Stupak, L. C. Andrade, R. T. López, Material Flow Analysis in a cooked mussel processing industry, *Journal of Food Engineering*, 2012, **113**, 100-117, doi: 10.1016/j.jfoodeng.2012.05.014.
- [5] N. N. Alves, G. B. Messaoud, S. Desobry, J. M. C. Costa, S. Rodrigues, Effect of drying technique and feed flow rate on bacterial survival and physicochemical properties of a non-dairy fermented probiotic juice powder, *Journal of Food Engineering*, 2016, **189**, 45-54, doi: 10.1016/j.jfoodeng.2016.05.023.
- [6] W. Liu, J. Hu, X. Zhao, H. Pan, I. Ali Lakhari, W. Wang, Development and experimental analysis of an intelligent sensor for monitoring seed flow rate based on a seed flow reconstruction technique, *Computers and Electronics in Agriculture*, 2019, **164**, 104899, doi: 10.1016/j.compag.2019.104899.
- [7] R. B. Shah, M. A. Tawakkul, M. A. Khan, Comparative evaluation of flow for pharmaceutical powders and granules, *AAPS PharmSciTech*, 2008, **9**, 250-258, doi: 10.1208/s12249-008-9046-8.
- [8] M. Gourdon, F. Innings, A. Jongsma, L. Vamling, Qualitative investigation of the flow behaviour during falling film evaporation of a dairy product, *Experimental Thermal and Fluid Science*, 2015, **60**, 9-19, doi: 10.1016/j.expthermflusci.2014.07.017.
- [9] I. Sinclair, Sensors and Transducers. *Elsevier Science*, Third Edition, 2001.
- [10] C. W. De Silva, Sensors and actuators: Engineering system instrumentation. *CRC Press*, ed. Second Edition, 2015.
- [11] M. Bartyś, R. Patton, M. Syfert, S. de las Heras, J. Quevedo, Introduction to the DAMADICS actuator FDI benchmark study, *Control Engineering Practice*, 2006, **14**, 577-596, doi: 10.1016/j.conengprac.2005.06.015.
- [12] L. F. Mendonça, J. M. C. Sousa, J. M. G. Sá da Costa, An architecture for fault detection and isolation based on fuzzy methods, *Expert Systems With Applications*, 2009, **36**, 1092-1104, doi: 10.1016/j.eswa.2007.11.009.
- [13] P. Subbaraj, B. Kannapiran, Fault detection and diagnosis of pneumatic valve using Adaptive Neuro-Fuzzy Inference System approach, *Applied Soft Computing*, 2014, **19**, 362-371, doi: 10.1016/j.asoc.2014.02.008.
- [14] M. Karpenko, N. Sepehri, D. Scuse, Diagnosis of process

- valve actuator faults using a multilayer neural network, *Control Engineering Practice*, 2003, **11**, 1289-1299, doi: 10.1016/s0967-0661(02)00245-9.
- [15] A. Diez-Olivan, J. del Ser, D. Galar, B. Sierra, Data fusion and machine learning for industrial prognosis: trends and perspectives towards Industry 4.0, *Information Fusion*, 2019, **50**, 92-111, doi: 10.1016/j.inffus.2018.10.005.
- [16] K. Tidriri, T. Tiplica, N. Chatti, S. Verron, A generic framework for decision fusion in fault detection and diagnosis, *Engineering Applications of Artificial Intelligence*, 2018, **71**, 73-86, doi: 10.1016/j.engappai.2018.02.014.
- [17] Y. Tian, Z. Wang, L. Zhang, C. Lu, J. Ma, A subspace learning-based feature fusion and open-set fault diagnosis approach for machinery components, *Advanced Engineering Informatics*, 2018, **36**, 194-206, doi: 10.1016/j.aei.2018.04.006.
- [18] Z. Xuewei, L. Hanshan, Research on transformer fault diagnosis method and calculation model by using fuzzy data fusion in multi-sensor detection system, *Optik*, 2019, **176**, 716-723, doi: 10.1016/j.ijleo.2018.09.017.
- [19] X. Zhou, T. Peng, Application of multi-sensor fuzzy information fusion algorithm in industrial safety monitoring system, *Safety Science*, 2020, **122**, 104531, doi: 10.1016/j.ssci.2019.104531.
- [20] G. Zhao, A. Chen, G. Lu, W. Liu, Data fusion algorithm based on fuzzy sets and D-S theory of evidence, *Tsinghua Science and Technology*, 2020, **25**, 12-19, doi: 10.26599/tst.2018.9010138.
- [21] Z. Ge, Y. Liu, Analytic hierarchy process based fuzzy decision fusion system for model prioritization and process monitoring application, *IEEE Transactions on Industrial Informatics*, 2018, **15**, 357-365, doi: 10.1109/TII.2018.2836153.
- [22] L. Shrinivasan, J. R. Raol, Interval type - 2 fuzzy - logic - based decision fusion system for air - lane monitoring, *IET Intelligent Transport Systems*, 2018, **12**, 860-867, doi: 10.1049/iet-its.2017.0095.
- [23] X. Liu, L. Ma, J. Mathew, Machinery fault diagnosis based on fuzzy measure and fuzzy integral data fusion techniques, *Mechanical Systems and Signal Processing*, 2009, **23**, 690-700, doi: 10.1016/j.ymsp.2008.07.012.
- [24] S. Majumder, D. K. Pratihari, Multi-sensors data fusion through fuzzy clustering and predictive tools, *Expert Systems With Applications*, 2018, **107**, 165-172, doi: 10.1016/j.eswa.2018.04.026.
- [25] M. K. Al-Sharman, B. J. Emran, M. A. Jaradat, H. Najjaran, R. Al-Husari, Y. Zweiri, Precision landing using an adaptive fuzzy multi-sensor data fusion architecture, *Applied Soft Computing*, 2018, **69**, 149-164, doi: 10.1016/j.asoc.2018.04.025.
- [26] J. Esteban, A. Starr, R. Willetts, P. Hannah, P. Bryanston-Cross, A Review of data fusion models and architectures: towards engineering guidelines, *Neural Computing and Applications*, 2005, **14**, 273-281, doi: 10.1007/s00521-004-0463-7.
- [27] H. B. Mitchell, Data fusion: concepts and ideas, *Springer Science & Business Media*, ed. Second Edition, 2012.
- [28] T. J. Ross, Fuzzy Logic with Engineering Applications. *Wiley*, 2010, doi: 10.1002/9781119994374.
- [29] J. R. Raol, Multi-Sensor Data Fusion with MATLAB, *CRC press*, ed. First Edition, 2009.
- [30] N. I. LabVIEW, PID and Fuzzy Logic Toolkit User Manual, 2009.
- [31] F. Previdi, T. Parisini, Model-free actuator fault detection using a spectral estimation approach: the case of the DAMADICS benchmark problem, *Control Engineering Practice*, 2006, **14**, 635-644, doi: 10.1016/j.conengprac.2005.04.001.
- [32] P. Przystalka, W. Moczulski, Methodology of neural modelling in fault detection with the use of chaos engineering, *Engineering Applications of Artificial Intelligence*, 2015, **41**, 25-40, doi: 10.1016/j.engappai.2015.01.016.
- [33] L. Ma, X. Li, C. Lei, W. Wang, *Chinese Automation Congress (CAC)*, 2017, 2784-2788, doi: 10.1109/CAC.2017.8243249.

Author information



Mrs. Bhagya R Navada completed her graduation from Kuvempu University in the year 2005, and post-graduation from Manipal University in the year 2011. She is working as a faculty in the department of Instrumentation and Control Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India. Her research interests include fault diagnosis, automation, sensor fusion, and image processing.



Dr. Santhosh K Venkata received his bachelor's and Master's from Visvesvaraya Technological University, Belgaum in 2004 and 2006. He received his Ph.D. from the National Institute of Technology, Silchar in the year 2013. He is currently working as Associate Professor, in the Department of Instrumentation and Control Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India. His research interests are in the area of sensor fusion, smart sensor, and fault detection and isolation.

Publisher's Note: Engineered Science Publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.