



Is Fault Detection and Diagnosis in Pneumatic Actuator A Topic of Concern?

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ABSTRACT

The present civilization highly depends on industrial products and hence there is an increased demand for the same. Therefore, each industry is trying to increase its production output without hindering the quality. Maintenance of plant health is essential to improve the production rate without any loss. Industrial processes require monitoring of every element as their consistent behavior is a fundamental concern. Any deviation in the working of these components may alter the quality of the end product, causing a huge loss for the industry. Therefore, monitoring and finding the root cause for irregular behavior of industrial processes is a requisite for avoiding any future loss. In this paper, an attempt is made to present types of faults, types of pneumatic actuator faults, and different techniques used for the detection and isolation of faults. Simulation work is carried out to generate stiction behavior in the control valve using the Choudhury stiction model. Valve stiction behavior for different values of stick band and jump values are discussed in this paper. A comparison of several techniques used for the detection of faults based on two performance indices namely true detection rate and false alarm rate has been given at the end of this paper. From these techniques, it is observed that these indices are interdependent, such that an increase in the detection rate increases the false detection rate and increases detection time.

1. Introduction

Industries play a vital role in fulfilling the day-to-day needs of humans. Industries will invest their money, time, and human power to cater to the needs of customers with many process stations each for fulfilling a particular task. These processes will have a set of operations to be performed to achieve the set target with a deadline. To reduce the requirement of human power and manual delay, gradually industrial processes are automated leading to improved speed of the process. In industries, to achieve a specific product, controlling various variables is imperative. Control of these parameters

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will be achieved through a control loop. A general control loop comprises a plant, controller, measurement device, and a final control element as shown in Figure 1. A mechanical device that causes the change in plant parameters based on the control signal from the controller is a final control element also referred to as an actuator. Actuators could be electric, hydraulic, or pneumatic type based on the application [1]. In the control loop, Process Variable (PV) is measured from the process block, it is compared with a preset SetPoint (SP) value, and based on the difference the controller provides Control Output (CO). The CO activates the actuator to generate the Manipulating Variable (MV). This process continues to maintain the process variable to a preset value. As the pneumatic actuator is made of mechanical/electrical components, there are possibilities that they will have wear and tear over the period of its operation. As the actuator is in direct contact with the physical process, any small variation in actuator behavior affects the process behavior noticeably. This will give rise to deviation in process behavior which can be referred to as the faulty nature of the component. The effect of a fault on the process may differ based on the severity and type of fault, but the quality of the end product may get affected to a larger extent. Hence, monitoring and maintaining of actuator health are essential in the industrial processes.

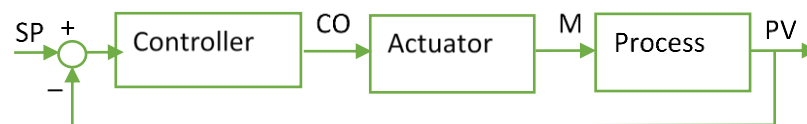


Fig. 1. General control loop

Because of the increasing demand for process monitoring, maintaining the health of process components is the key requirement. To know the behavior of the process, getting its parameter information is necessary which is accomplished by using appropriate sensors or soft sensing techniques. This section overviews research work done in the area of soft sensor development, sensor/actuator fault detection. Jinlin Zhu *et al.*, [2] reported the estimation of a process variable through a soft sensor model based on the mixture of the robust supervised probabilistic principal component analysis method. The design of an estimation observer for a nonlinear discrete-time system using a modified fuzzy was highlighted in Xie *et al.*, [3]. Takagi Sugeno method was used for the design of observers for the estimation of fault using maximum priority-based switching law. Analysis of degradation levels of the aeronautical pneumatic actuator is stated in Graves *et al.*, [4] to understand the signatures of 5 types of faults namely leakage, friction, backlash, charge clogging, and discharge clogging. Here, the pattern of hysteresis of different indices is analyzed, and based on its signature, faults were detected. Lin *et al.*, [5] discussed an approach for the development of soft sensors using a robust multivariate technique through online measurement. Heredia *et al.*, [6] reported a model-based approach for the detection of sensor and actuator faults in a helicopter system. An observer-based system was used for generating residuals, and this method was tested in simulation and experimentation. Alireza *et al.*, [7] stated actuator and sensor fault detection using an adaptive observer-based technique in unmanned aerial vehicles. Esmaeil and Khorasani [8], detailed a method for actuator and sensor fault detection, estimation, and isolation in discrete-time linear systems. This being a data-driven method involves input and output data collected from the system and estimates Markov parameters. A method for the detection of actuator faults in a wastewater treatment plant using a model-based method is summarised in [9]. Here, change in the plant state because of change in actuator faults was studied, and based on the estimated and actual value, residuals were calculated. This method was tested with simulation results which gave a fast and accurate detection rate of fault.

Many researchers have worked in the area of fault detection, isolation, and fault identification, or all of them forming diagnosis techniques as this is very important in industrial process monitoring. Some articles involving fault detection techniques in different actuation systems have been reported here. Peng *et al.*, [10] reported monitoring and detection of faults through real-time simulation in nuclear powerpoint pressurized water reactors. Here, Incipient faults were detected by the actuators by using a thresholding technique. Fault severity was detected by analyzing the compensation from the control system and residual trends. Li *et al.*, [11] analyzed a method for monitoring process parameters that were weakly correlated. Sheriff *et al.*, [12] discussed a method to improve the performance of a fault detection system by reducing the effect of uncertainties in the data. Zang *et al.*, [13] summarized an algorithm formed with a combination of wavelet de-noise technique with PCA for fault detection in a feedwater system. Hongquan *et al.*, [14] reported a fault detection technique for the detection of an incipient fault in the industrial processes. Here, two techniques namely moving average and exponentially weighted moving average were applied as smoothing techniques in multivariate process monitoring. Turner *et al.*, [15] communicated a fault detection system used in residential buildings for detecting faults in heat, ventilation, and air conditioning systems. A data-driven approach was used for estimation of building model, its heat, ventilation, and air conditioning system model for comparing the system performance with normal performance. Detection of electro-hydraulic servo system leakage fault is discussed in Sharifi *et al.*, [16]. Leakage of fluid cannot be measured directly from sensor output thus pressure signals were used as data and were mapped into another space and a nonlinear representation approach was used to detect the fault.

In this section fault detection and isolation techniques that have been implemented across various processes are reported here. Nozari *et al.*, [17] have put forward a data-driven method for fault detection and isolation using ensemble classification methods. A comparison of all classification methods individually and ensemble results were highlighted. Jun-Jie and Zhen [18] reported a fault detection and isolation method for the actuator mechanism by using a sliding mode observer. To differentiate disturbances from actuator faults, models for each actuator were considered separately. The actuator mechanism comprises numerous actuators thus observers were designed for each actuator and are used to detect actuator faults. Madrigal-Espinosa *et al.*, [19] detail a method for the detection and isolation of sensor faults in a thermal power plant boiler system. Adaptive thresholds were used to minimize the false alarm rate. Fault detection system output was used to take necessary action on other sensors associated with the steam generator for improving the efficiency of the monitoring procedure. A scheme for detection and isolation of actuator fault in a quadrotor was reported in Avram *et al.*, [20]. An estimator detected actuator fault by observing the behavior of the system for abnormalities. The actuator fault model was obtained for fault isolation.

Fault diagnosis is a wide area that involves detection, isolation, and identification of faults. Research on these topics has been discussed in this section. Mehennaoui *et al.*, [21] reported a fuzzy neural scheme for sensor fault diagnosis in nonlinear systems. It focuses on fuzzy logic as a local identification method and neural network as a global identification method to detect sensor faults in a three-tank process. Ramdani and Doghmane [22] described a multimodal approach for fault diagnosis of three tank system. Residuals were generated and then evaluated by using a fuzzy inferential process. Faults like pipe blockages, pump fault, level sensor faults, and tank leakages have been detected. Zhang [23] discussed a method to diagnose distillation column faults with robustness for sensor distortion. Lin *et al.*, [24] reported a method for diagnosis of process fault using extended state observer and soft computing techniques. Here, a three-tank system has been considered as a case study to diagnose process faults by observing the rate of change of general dynamics of the process. Mrugalski and Witczak [25] reported a method for diagnosis of actuator fault using state-

space group method data handling neural network model. This model was estimated using the Unscented Kalman Filter (UKF) that facilitates the calculation of output adaptive threshold using which actuator fault was diagnosed. A strategy for diagnosis of faults and their rate of occurrence in computer numeric control machine is reported in Zhang *et al.*, [26]. The model of faults and also the structural model was used to detect the propagation of faults. Page rank algorithm evaluates the effects of machine tools failure.

After a fault is isolated, the next step is to identify its size and severity, forming detection and identification techniques. Some research work in the area of fault detection and identification have been discussed here. Fernando and Surgenor [27] have put forward a fault detection and identification technique using an unsupervised neural network for fault detection of an automated assembly machine. Caliskan *et al.*, [28] discussed the identification of loss of control effectiveness and magnitude of stuck faults in B747 aircraft using an adaptive modified two-stage Kalman filtering algorithm.

Research in the area of fault detection has gained high importance in monitoring. Researchers also started to think about limiting the damages due to faults. Working on fault-tolerant and compensation algorithms that monitor the functional blocks and components of the system have gained research importance. Research work in the area of fault-tolerant control has been discussed in this section. Li and Jin [29] reported a fault-tolerant control scheme to detect lock in place and loss of effectiveness faults of the actuator. Here false alarms and delays between detection and alarm were detected. Yang and Dongik Lee [30] reported a fault-tolerant control technique for enduring the failure of the actuator using a network based on the control allocation actuator management technique. Based on the classification of fault occurrence, five parameters of the aircraft actuator were measured. López-Zapata *et al.*, [31] reported a fault-tolerant control system for the detection of actuator faults in a heat exchanger system. In this system, the Kalman filter estimates the control valve output for the detection of the fault. After the fault detection, the model following control law helped to avoid disturbances in the process, thereby compensating the fault. Wenying *et al.*, [32] described an architecture for fault-tolerant control and detection of actuators and sensors fault in distributed parameter systems. In Zou *et al.*, [33], a model predictive fault-tolerant control technique has been reported for a batch process. Here genetic algorithm optimizes the state vector matrix to have a better control action on actuator faults and unknown disturbances.

A fault compensation method for time-varying actuator faults in the nonlinear, fractional-order system was addressed in Bataghva and Hashemi [34]. Here, instead of the detection of faults, a compensation method using an adaptive sliding mode synchronization scheme was explained. Vargas-Martínez *et al.*, [35] discussed six methods of fault detection schemes that were developed for fault-tolerant control to detect abrupt and gradual faults in a heat exchanger plant. A model reference adaptive control was combined with six different controllers to develop six fault detection schemes. Guilherme *et al.*, [36] stated three immune systems in knowing faulty and faultless conditions for fault detection and isolation schemes. The three fault immune approaches briefed are toll-like receptor algorithm, dendritic cell algorithm, and danger model algorithm. These methods require clear prior knowledge about the system which is difficult and should be obtained by the experts. Hence most of the fault detection methods, fault immune systems are not adopted. Training of data is required in both dendritic cell and toll-like receptors method for forming the decision rules and had performed satisfactory fault detection. The danger algorithm showed a large delay in the detection of the fault, and the detection procedure is based on the danger signal.

2. Pneumatic Actuator

A pneumatic actuator is a device that converts compressed air pressure into motion, which can be linear or rotary. A pneumatic actuator comprises a control valve, pneumatic servomotor, and positioner. The schematic diagram of the linear pneumatic actuator is shown in Figure 2. The control signal is converted into pressure using a current to pressure converter. Air pressure is applied as supply causing movement of the diaphragm that moves the stem downwards causing the change in the valve position. Change in the valve position alters the liquid flow rate at the output of the valve [38]. As it has many more sub-components in it, proper working of all these components is very important hence there is a necessity to monitor these components. If the behavior of process components has deviated from their normal behavior, then that component can be identified as faulty.

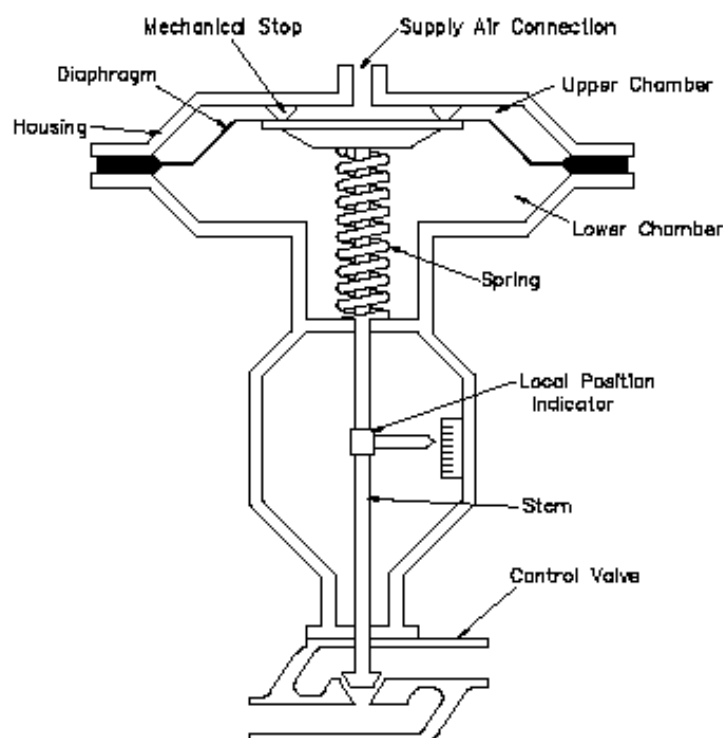


Fig. 2. Air to close pneumatic actuator [37]

Thus, the detection of faults in a process loop is the key requirement to avoid hampering of final product and safety of the plant. A detailed discussion on faults, major categories of faults, terminologies related to faults, and pneumatic actuator faults is presented in subsequent sections.

2.1 Faults

Faults are classified into abrupt and incipient faults based on the time taken for the development of fault. Faults that show the rapid development of effect are termed to be an abrupt fault. Detecting incipient faults is difficult because of their slow development of effect [39]. Figure 3(a) and (b) shows the graphical explanation of abrupt and incipient faults [40].

Terms associated with faults and its detection are discussed in the following section.

- Fault detection[FD]: A process of detection of the incidence of faults in the functional components of the process, which results in improper and undesired behavior of the complete system.
- Fault isolation: Classification and detection of different fault sources.
- Fault analysis or identification: Finding the type, cause, and size or severity of faults.
- Fault detectability: Gives the information regarding the changes in the system behavior due to a fault. It should be indicated independent of the uncertainties of the model, system input variables, and disturbances. If the incidence of a fault causes variation in the normal behavior of the system irrespective of its type and size, then that fault is detectable.
- Fault isolability: Two or more separable faults are called as isolable faults [41].
- Fault identifiability: Representation of system structure which is required to reconstruct the faults from input and output of the system is considered as fault identifiability. It also characterizes the mapping of system output to a concerning fault. A fault is identifiable if the mappings are unique [42].
- Fault distinguishability: Faults are distinguishable if the effect of each fault has its characteristic identified as a signature of the fault. Each fault has its signature and if the signatures are similar for more than one fault then they are called an indistinguishable fault. Some faults are not indistinguishable and not fully distinguishable such faults are called conditionally distinguishable [42].

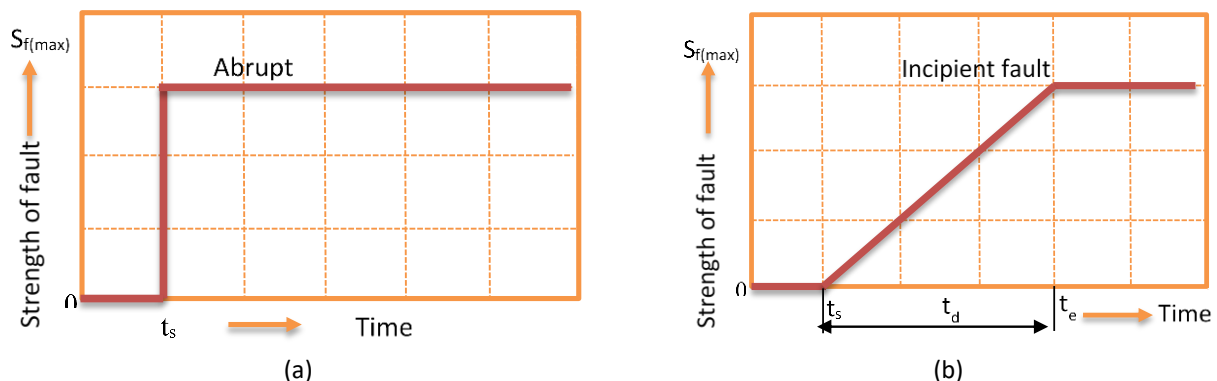


Fig. 3. (a) graphical understanding of abrupt fault (b) graphical understanding of incipient faults.
 Notion: t_s – start time of the fault, t_e – end time of the fault, t_d – development time, $S_{f(max)}$ – maximum strength of fault

2.2 Pneumatic Actuator Faults

Failure of the final control element is often a common problem faced in industries. Malfunctioning of actuators may disturb the process in the long term or may lead to shut down of the process, thus affecting the quality of the product causing an economic loss. The life of an actuator is influenced mainly by the environment where it is installed. Usually, they are installed in harsh locations like high pressure, temperature, humidity, vibration, chemical solvents, pollution, etc.

There are many types of faults associated with a pneumatic actuator and based on the source of fault they are categorized into positioner faults, control valve faults, servomotor faults, and general or external faults [40] as presented in Figure 4.

The methods and techniques developed for fault detection of the pneumatic actuator are tested with a benchmark system to standardize and validate. The most commonly used benchmark is Development and Application Methods for Actuator Diagnosis in Industrial Control Systems

(DAMADICS), which was used in fault diagnosis studies of the actuator in a sugar factory at Lublin, Poland [40]. Introduction to a benchmark system and its use for testing fault detection and identification [FDI] methods and 19 ($f_1 - f_{19}$) types of actuator faults have been listed under four categories of pneumatic actuator faults as depicted in Figure 5. Faults $f_1 - f_7$ are categorized into control valve faults, $f_8 - f_{11}$ are categorized into servomotor faults, $f_{12} - f_{15}$ as positioner faults, and $f_{16} - f_{19}$ as other faults. Düşteğör *et al.*, [43] reported the analysis of structural fault isolability for the DAMADICS benchmark system. Totally 19 faults stated in DAMADICS were considered checking the isolability by forming isolation matrix as more than one fault may have the same signature. Kościelny *et al.*, [42] discussed terminologies used in fault detection and two more faults namely pressure sensor fault at control valve inlet(f_{20}) and control valve outlet(f_{21}) were added under other faults category in DAMADICS benchmark hence total 21 faults were considered in this study. Three valued evaluation schemes for residuals i.e. $\{-1, 0, 1\}$ were used for finding the signature of faults. Signatures for 21 DAMADICS actuator faults were tabulated using a three-valued evaluation scheme. A comparison regarding sensitivity between two-valued and three-valued evaluation scheme was also discussed.

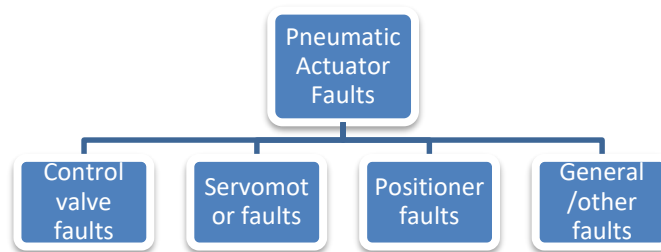


Fig. 4. Pneumatic actuator faults categories

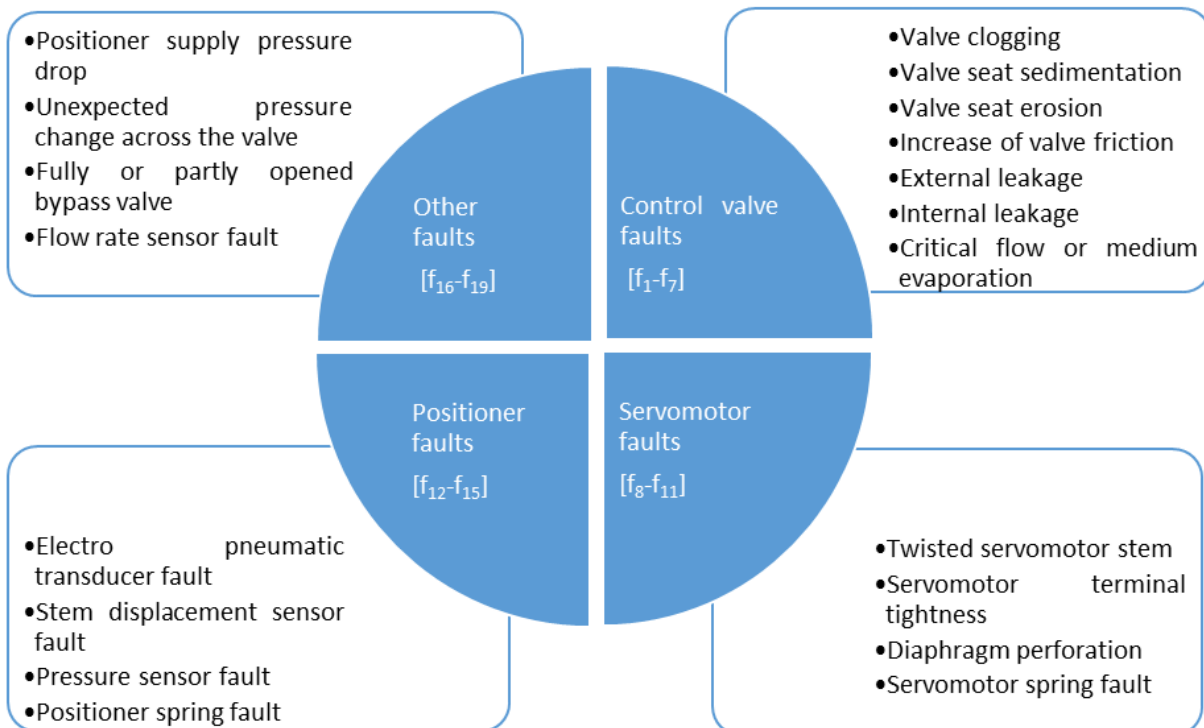


Fig. 5. Faults categorization concerning the source of the fault

2.2.1 Pneumatic actuator fault categories

Research articles on the detection of faults for four different categories of pneumatic actuators faults have been discussed in this section. In most situations, a single actuator fault is observed as multiple faults occur rarely.

- Control valve faults

Among the four categories of pneumatic actuator faults, control valve faults can be considered as the major faults. Servomotor, positioner, and other faults have also gained research importance other than the control valve faults detection. Most of the research works have concentrated on the detection of not only control valve faults but also servomotor, positioner, and other faults. In Table 1, research work carried out to find more than one category of pneumatic actuator faults has been tabulated. Few research articles that highlight detection techniques for control valve faults that are not tabulated in Table 1 are [36, 41, 43, 59-62].

- Servomotor faults

Some of servomotor faults have been detected in [41, 43, 47-48, 53-55, 58-62]. Karpenko *et al.*, [63] discussed the detection and identification of actuator faults and their severity using a neural network based on observation of performance parameters of a typical control valve step response. Depending on the particular values of the performance parameters, each fault and its severity was found. A neural network was trained to estimate the fault intensities for which they were not trained. Bouamama *et al.*, [64] reported a method using bond graphs to develop fault detection and isolation algorithm. The bond graph model was considered as a graphical modeling language. Here, two faults: inlet pressure sensor fault and diaphragm perforation faults were simulated and detected.

- Positioner faults

Some positioner faults were detected in [36, 41, 43-45, 47-49, 58, 59-62, 64]. Mrugalski *et al.*, [65] reported a fault identification method based on a multi-layer perceptron neural model. A neural model of the system with model uncertainty was calculated regarding the observed data. Here, flow rate sensor fault, positioner supply pressure drop, and unexpected pressure drop across the valve were the faults detected concerning the DAMADICS benchmark system. Positioner faults have been detected in many papers as given in Table 1

- General /other faults

In many of the above discussed papers, algorithm for detection of general faults also have been reported in [36, 41, 43, 45, 47-49, 53-55, 58-63, 65]. Wiczaka *et al.*, [66] reported an approach based on a group method of data handling neural networks for robust fault detection. Here neural network with relatively small modeling uncertainty was developed. The algorithm is used to detect faults and to classify them as small, medium, big, and incipient faults. Bezzera *et al.*, [67] detailed an approach for the detection of anomaly faults in industrial processes. Here, typicality and eccentricity data analytics approach for fault detection has been applied. This method was used for considering some of its advantages like no requirement of prior knowledge about the process data, fastness because of a recursive algorithm, and the reduced computational work. Positioner supply pressure drop, the unexpected pressure drop across the valve, partly opened bypass valve and flow rate sensor fault under general faults category of actuator faults were detected. Results signified that this method was suitable for detecting abrupt faults as incipient faults were not causing a significant change.

Table 1

Articles with more than one category of pneumatic actuator faults

Reference	Findings	Faults detected	Method/ technique
Puig <i>et al.</i> , [44]	The observer sets a priori bound on disturbances and uncertain parameters and creates estimated states which are steady with the prior bounds and present measurements.	Diaphragm perforation faults, spring fault, valve clogging, and rod displacement actuator faults.	Interval observer.
Uppala <i>et al.</i> , [45]	Faults were grouped into small, medium, and high rates.	valve clogging, valve seat sedimentation, critical flow, stem displacement sensor fault, unexpected pressure change across the valve, fully or partly opened bypass valve and flow rate sensor faults	Neuro-fuzzy multiple modeling with robust optimal decoupling of the observer. Fuzzy model
Mendonca <i>et al.</i> , [46]	Reported a model-based approach for FDI	Critical flow, valve clogging, flow rate sensor fault, internal leakage, and valve seat erosion	Fuzzy model
Laurentys <i>et al.</i> , [47]	Danger signals are the signals that were generated when the performance of the process components was not under normal behavior and was used to detect the fault occurrence in the process.	Valve clogging, critical flow, servomotor diaphragm perforation, positioner spring fault, and unexpected pressure change across valve fault.	Intelligent immune-based approach
Chopra <i>et al.</i> , [48]	Reported an approach for classification of overlapping actuator fault classes.	Valve seat sedimentation, seat erosion, and valve clogging actuator faults	Self-Organizing Map [SOM]
Subrahmanya and Shin [49]	Proposed an observer-based method for detection and diagnosis of actuator fault.	Valve clogging, unexpected pressure drop, flow rate sensor faults	Neural network
Kowsalya and Kannapiran [50]	The backpropagation algorithm was used to train ANN and the performance improved by using PCA.	Valve clogging, valve seat sedimentation, internal leakage valve tightness faults	Artificial Neural Network [ANN]
Subbaraja and Kannapiran [51]	A backpropagation algorithm was used to train the neural network.	Valve clogging	ANN
Subbaraja and Kannapiran [52]	A comparison between the adaptive neuro-fuzzy inference system and multilayer feed-forward neural network is given.	All control valve faults	Adaptive Neuro-fuzzy inference system
Prabakaran <i>et al.</i> , [53]	The fault detection algorithm for three actuator faults was detailed.	Incorrect supply pressure, diaphragm leakage and actuator vent blockage	Fuzzy logic [53], neural network algorithm [54] and SOM [55]
Ahmed Hafaifa <i>et al.</i> , [56]	ANN was trained with system inputs and outputs using an adaptive supervised learning method.	Valve clogging and rod displacement sensor faults	ANN
Lemos <i>et al.</i> , [57]	Adaptive fault detection and diagnosis methods for a dynamic system using a model-free approach have been reported.	Valve clogging, valve seat sedimentation, unexpected pressure change across the valve and flow rate sensor fault	Fuzzy classifier
Chopra and Vajpai [58]	Reported an approach for fault diagnosis based on stochastic gradient boosted decision tree method. This method was compared with the other methods for a percentage of misclassification.	Unconditionally indistinguishable faults categories namely, {f ₂ , f ₅ , f ₇ }, {f ₃ , f ₆ , f ₁₈ }, {f ₄ , f ₈ }, {f ₉ , f ₁₀ }, {f ₁₃ , f ₁₅ }	Gradient boosted decision trees

2.2.2 Abrupt and incipient faults

Among 19 DAMADICS faults, depending on the way the fault variation occurs, actuator faults have been categorized into 9 only abrupt, 5 only incipient, and 5 both abrupt and incipient faults. Hence (26+26) % of total actuator faults come under incipient fault whereas rest (26+48) % come under abrupt faults as represented in Figure 6 [40]. Some faults are categorized in both incipient and abrupt faults as represented in Figure 6. Detection of abrupt faults is comparatively easier as the effect is noticeable but detection of incipient faults is difficult as the effect is slow and gradual hence it is hard to observe the effect.

Detection of abrupt and/or incipient faults has been reported in many research articles. Overall actuator faults have been discussed in the following section. Some researchers have reported work on detecting abrupt and incipient faults that have been tabulated in Table 2 with observations of detected faults.

Table 2
 Incipient and abrupt fault detection methods

References	Observation	Faults detected
Previdi and Parisini [41]	Squared coherency function is sensitive to particular changes in the dynamics of the plant through which fault was detected.	All abrupt faults were detected
Calado <i>et al.</i> , [59]	A fault detection technique using a fuzzy qualitative process simulator was reported. Fault isolation was carried out using the hierarchical structure of a fuzzy neural network.	All abrupt and incipient faults were detected. Some faults were detected only in dynamic conditions.
Cosmin <i>et al.</i> , [60]	The application of a fuzzy classifier for finding one or more fault with more categories of each fault was detailed. This algorithm was tuned using various techniques out of which particle swarm optimization technique was reported to perform better.	Abrupt faults were detected. More than one fault was detected simultaneously.
Korbicz and Kowal [61]	A robust fault identification method based on the Takagi-Sugeno Neuro-fuzzy model for detection of actuator fault was developed.	All abrupt and incipient faults were detected except some undetectable faults like f_5 , f_9 , f_{12} , and f_{14}
Przystałka and Moczulski [62]	An approach for fault detection by developing a neural model of faultless state of the system using chaos theory was summarized. It was tested on all four categories of faults in the DAMADICS benchmark system.	All faults were detected except f_8 and f_{14}
Wang and Dalay [68]	An adaptive observer technique for actuator fault detection and diagnosis in deterministic systems was reported. Here, two observers, one fixed observer for abrupt fault detection and the adaptive observers for detection of abrupt faults with uncertainty.	<ul style="list-style-type: none"> • Abrupt faults (with and without uncertainty) • This method was not verified with the DAMADICS benchmark.
D'Angelo <i>et al.</i> , [69]	Changepoint detection in time gives information on physical variables in a steady-state of the dynamic system. This methodology was tested with the DAMADICS benchmark system. A Fuzzy Bayesian methodology was used to find change point detection in a dynamical system.	Incipient faults were detected namely f_6 , f_9 , f_{11} , f_{13} , f_{17} , f_{18}

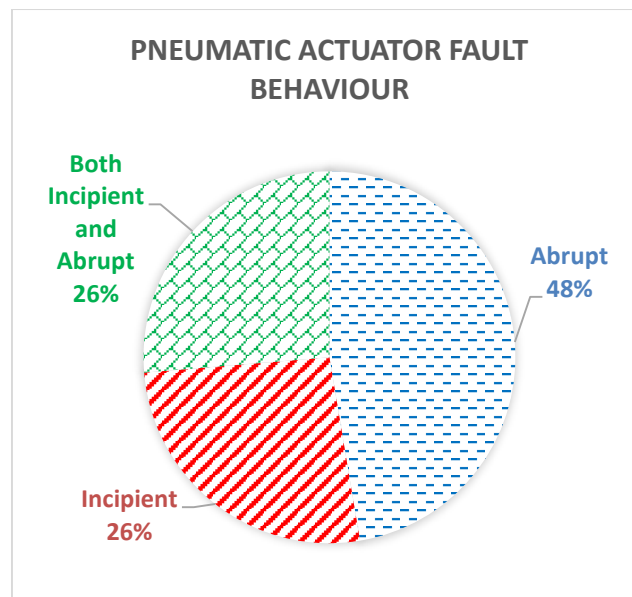


Fig. 6. A percentage representation of abrupt and incipient faults

3. Techniques Used for Fault Detection

Numerous techniques are used for pneumatic actuator fault detection based on various diagnostic methods such as hardware redundancy, plausibility test, analytical/software redundancy, and signal processing, and they are symbolized in Figure 7 [70]. Among these methods, hardware redundancy and plausibility test methods are rarely using methods because of their limitations. Analytical / software redundancy or model-based schemes and signal processing methods are the booming areas in the current scenario.

- Hardware redundancy based FDT: Here a redundant component is used to check the output from the process component. If process component output has deviated from the redundant component, then it is considered as the sign of occurrence of a fault. This method is highly reliable, provides direct fault isolation but the cost increases due to redundant components hence restricted to few applications [70].
- Plausibility test: some physical laws under which components of process works will be checked. If there is any deviation from the normal performance, it will result in plausibility loss. This test is mainly used for fault detection.
- Signal processing based FDT: In this scheme, it is assumed that some process signals carry information about the faults. This information is analyzed and considered as a sign of fault and fault diagnosis is attained by the appropriate signal processing. This method involves time-domain methods, frequency-domain methods, and statistical methods. These methods can also be used for the development of physical models of the system. Distinctive symptoms are time-domain functions like mean value, magnitude, envelope, trends, limit values or frequency domain functions like cepstrum, power densities, frequency spectral lines [41,97], cross-correlation [71-72], statistical [5, 14, 98-99], feature extraction [57, 100-102], and PCA [2, 10-12, 103-108], etc. This technique is generally used for the detection of faults in steady-state as the efficiency is limited for the dynamic system fault detection.
- Model-based FDT: The main intention of the model-based approach is to represent the process model in software to overcome hardware redundancy. The model of the process can be of qualitative or quantitative description of the steady behavior and process dynamics

using various process modeling techniques. Thus online behavior of the process can be reconstructed which is similar to the hardware redundancy. Hence, this concept is called software redundancy or analytical redundancy [70].

- In software redundancy schemes, the model of the process will run with the actual process with the same set of inputs. The model is expected to produce the same output as that of actual process output under fault-free conditions. Thus any apparent deviations from the model output indicate a fault in the process. To get this information, the measured process variable should be compared with their estimates provided by the process model. The difference between the actual system output and model output is labeled as the residual of the system. The Method of developing the estimates of process outputs and obtaining the difference between the estimates and process output is called residual generation. Successful fault diagnosis can be achieved by utilizing the residual information. In most of the systems, the working of components is checked with their model. Residuals will have a null value when the process is running under the normal and faultless condition and will have a nonzero value under faulty condition. A nonzero value of residual may result due to a noisy environment, disturbances, or modeling errors under normal working of the system. It is essential to use a suitable decision making procedure for distinguishing between the fault and unwanted disturbances. Several techniques have been developed namely fuzzy logic methods [24, 46, 53, 60-61, 69, 73-75, 109], neural network/machine learning methods [7, 21, 27, 35, 47-52, 54-56, 62-63, 65-66, 75-79, 110-112], fuzzy neural or neuro-fuzzy methods [23, 45, 59, 80, 113], SVM [81-82], discrete wavelet transform methods [83-84], bond graph methods [64, 85] and observer-based method [7, 26, 31, 68, 86-87, 114-117], Kalman filtering method [9, 22, 118] for fault diagnosis. The effectiveness of these methods is generally tested with a benchmark system.

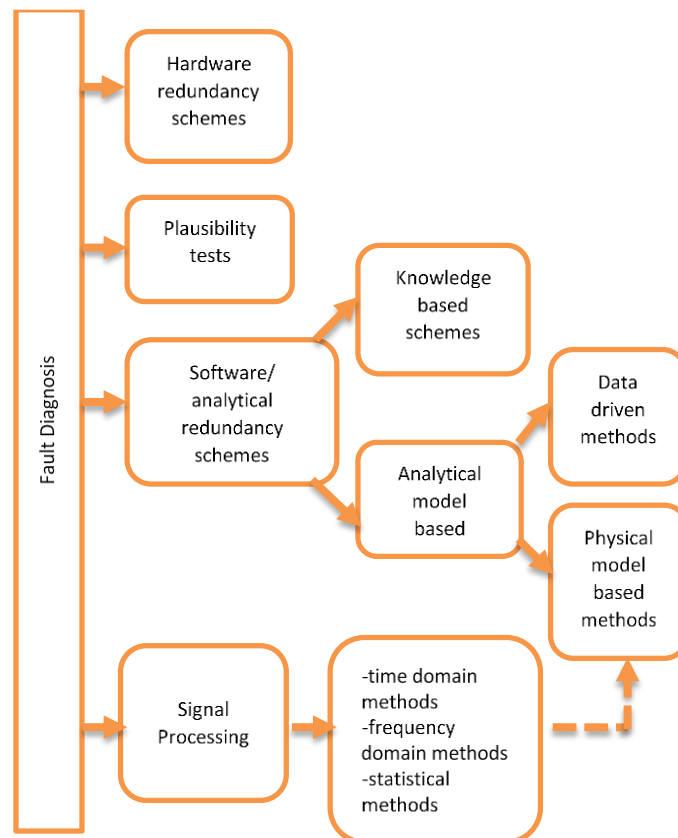


Fig. 7. Classification of fault diagnosis methods

4. Stiction Fault

As discussed in section 2.2.2, a total of 52% of faults out of 19 faults are incipient, and detecting these faults is a difficult process. Out of 52%, 26% of faults also behave abruptly in some situations. In the category of incipient faults, static friction offered to the movement of the control valve stem is the common fault in process industries. Static friction in valves is also called stiction causing limit cycles-oscillations in the form of periodic finite-amplitude instabilities that introduce non-linearity between manipulating variable and controller output in the process [88]. This accelerates equipment wear, increases variability in product quality, and leads to control system instability. When the applied force for changing the position of the valve is less than the static friction force, then the valve gets stuck completely. Due to the stuck valve, the controller output will be increased. As the applied force overcomes the static friction force, sudden change of valve from one position to another can be observed. At this point, the valve is influenced by dynamic friction force depending on the velocity. Thus applied force is more than the required hence the controller starts reducing the force and when the applied force overcomes the static friction force, the valve gets stuck in the new position. Stiction causes the sequence of stic and jump action of the valve, called stick-slip motion. The different regions of stiction have been illustrated in Figure 8. Here red dotted line represents the moving phase, the blue dotted line represents the constant phase and the green dotted line represents the slip jump phase [89]. This motion involves 3 steps of valve output:

- Constant: The valve output will be constant for the time when the valve is stuck in one position due to the existence of static friction force.
- Jump: Here, valve output changes suddenly/abruptly as the applied force overcome the static friction force.
- Motion: Gradual variation of the valve output exists as the applied force is opposed by dynamic friction force [72].

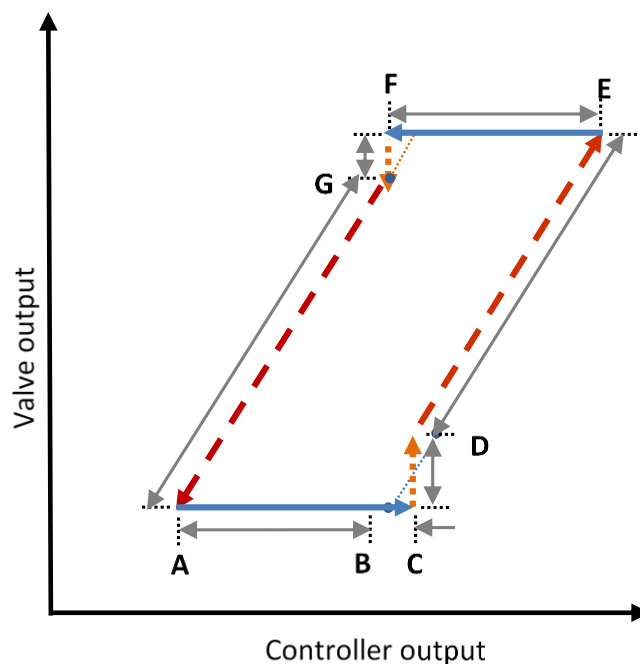


Fig. 8. Representation of different regions of stiction (where AB – Stickband(Constant), BC – Deadband, CD – Slip Jump, DE – Moving phase, EF – Stiction +deadband, FG – Slip jump)

Stiction is a nonlinearity component added to the system. Thus, to detect these effects, knowledge of its behavior is important. Many researchers have worked in the area of modeling and identification of stiction that is reported in this section. Choudhury *et al.*, [90] developed an empirical data-driven model of stiction by observing real-life data influencing the cause of stiction in control valves. Here, a new definition for static friction was proposed and terminologies related to stiction were reported. The developed model was validated based on the open-loop and closed-loop response of the model. Maruta *et al.*, [91] have reported two methods for the detection of stiction and development of valve stiction model. The developed model was validated by comparing the model output with the real plant data. Two methods for detection of stiction were reported in this paper based on different regions of characteristics between controller output and valve movement. Here, conventional methods of stiction detection and difference between disturbance and bad tuning were reported. Xie *et al.*, [92] proposed an enhanced version of the Choudhury data-driven stiction model that performs better compared to the Choudhury model. The original model was passing only seven industrial standard architecture tests out of fifteen, indicating the necessity for model improvement. The output of the Choudhury model for 5 standard tests has been indicated in this paper. From this, it is inferred that the failure was mainly for three reasons. First, when the input signal applied to the valve changes its direction, secondly when the ramp pause ramp type of input signal is applied to the valve, thirdly when the initial position of the stem is different from assumed range. The model proposed here is named XCH model and the authors claim that this model passes all the stiction parameter tests. di Capaci *et al.*, [93] have reported a comparative description for modeling and detection of stiction in industrial control valves with different models. Here, modeling is achieved by considering the process as a linear part and stiction as a nonlinear part using a Hammerstein system. The process with stiction was modeled using 5 identification techniques for modeling of a linear process and two techniques for nonlinear stiction modeling. Two parameters one representing the stickiness and the other representing the level of jump in process variables are measured to quantify the stiction into two categories namely, low stiction and high stiction. di Capaci *et al.*, [119] also reported a stiction identification method using a smoothed model without using discrete statements.

Some researchers have contributed to the field of stiction detection that is reported in this section. Horch [71] discussed a method of detecting stiction in control valves by computing cross-correlation between loop output and the control signal. Static friction results in a shift in the signals by around $\pi/2$ which produces an odd function for cross-correlation. The presence of other disturbances produces an even function for cross-correlation. Thus the occurrence of odd cross-correlation function implies the presence of stiction in control valves. This method was tested using industrial data for the occurrence of oscillations. Rossi *et al.*, [72] reported the influence of stiction in actuators on the performance of process loop and also discussed three types of techniques: namely cross-correlation, bi-coherence, and relay technique for detection of stiction. These three techniques were applied to real plant data and from the results obtained it was determined that the bi-coherence method gives better performance compared to the other two. Yamashita [94] proposed a method for detecting stiction in valves by observing the qualitative movements of the input-output plot. Here a stiction index was used to detect stiction and also to distinguish whether stiction causes from a poor controller or because of external disturbance. This method was stated as better performing when compared with the autocorrelation between loop output and controller output for the detection of stiction. Zakharov *et al.*, [95] proposed an autonomous system for the detection of valve stiction based on data sequences. Four stiction detection algorithms namely cross-correlation method, area-ratio method, histogram methods, and curve fitting methods were used. Indices used for enumerating the feature of data sequences. Based on these indices, one of the 4 stiction detection

algorithms was selected and the fault was detected according to the selected algorithm. Daneshwar and Mohd Noh [73] proposed a fuzzy clustering-based method for detection and diagnosis of stiction in the control loop. Here, detection of stiction was done firstly by finding the occurrences of loop non-linearity and secondly by framing an index based on which the reason for nonlinearity was found. Zhanyang *et al.*, [83] reported a data-driven non-invasive method for the detection of valve stiction using wavelet technology. Data was decomposed into different resolution scale through discrete wavelet transform [DWT] and by analyzing these wavelet coefficients, variations of the controlled variable were observed. From the de-noised data, features of valve stiction patterns were extracted to calculate the probability of valve stiction.

4.1 Case Study

Introducing stiction in a real plant is very difficult as it may damage the valve components due to the wear and tear process. So to understand the behavior of stiction fault, a data-driven model referred to as the Choudhury model is selected. The data-driven model has parameters that can be directly related to the plant data and it produces the same behavior as the physical model. The model needs only an input signal coming from the controller, three parameters stick band, dead band, and slip jump values. It is easier to understand the stiction behavior from the model for different values of stick band, dead band, and slip jump. In the data-driven model, the parameters are easy to choose and the effects of these parameter changes are simple to realize.

Figure 9 shows the signal and logic flow chart of the Choudhury data-driven stiction model [90]. The data-driven model takes data and parameters from the plant and gives results the same as the physical model. The model needs only slip jump, dead band/stick band values, and an input control signal to provide stiction output.

Controller output in the form of current from 4-20mA is initially converted into 0-100 percentage of valve movement and is given as input to the stiction model. If valve movement is less than 0, then output is considered to be '0' and if valve movement is more than 100% then the valve is considered to be fully saturated i.e., fully open or fully closed. If valve travel lies in between 0-100% then the algorithm calculates the slope of the control signal. The output of the stiction block is mainly decided based on the sign of the slope of the control signal. If the input signal is increasing, then the sign of slope will be positive and if it is decreasing, then the sign of slope will be negative. If the input to the valve does not change then the sign function gives a '0' value, then the valve is considered as stuck. If the sign changes from positive to negative, then change in the direction of the input signal is observed and is considered as the beginning of the stick phase. Then the value input at this stick position is considered as 'xss'. If the sign of input signal changes and if the collective change of input overcomes the sum of deadband and stick band, then the valve slips and will start moving. If the input signal slope does not change and the collective change of input becomes greater than the jump, then the valve slips and valve movement starts.

Now, the valve may stick in the same direction upwards or downwards if and only if the input signal to the valve does not change or the sign does not change for two consecutive instants, which is usually uncommon in practice. For this situation or scenario, the sign(slope) changes to '0' from '-1' or '+1' and vice versa. The algorithm again detects here the stick position of the valve in the moving phase and this stuck condition is denoted with the indicator variable $I' = 1$. The value of the input signal when the valve gets stuck is denoted as xss. This value of xss is kept in memory and does not change until the valve gets stuck again. The cumulative change of input signal to the model is calculated from the deviation of the input signal from xss. The output is calculated using the Eq. (1).

$$\text{Output} = \text{input} - \text{sign}(\text{slope})(S - J)/2 \tag{1}$$

Depending on the values of 'S' and 'J', different stiction types can be obtained. These stiction types are explained below

- Dead band: If the value of 'J' is zero then there will not be any slip jump only dead band is observed.
- Stiction (Undershoot): If $J < S$, valve output will not be able to reach the input, and some offset can be observed between valve input and output.
- Stiction (No Offset): When the value of 'S' becomes equal to 'J', there will be stick-slip behavior and there will not be any offset between input and output. There will be a stick behavior until the input overcomes the friction force after that there will be slip movement.
- Stiction (Overshoot): If $J > S$, slip phase or jump phase causes a greater change in output which overshoots the valve input.

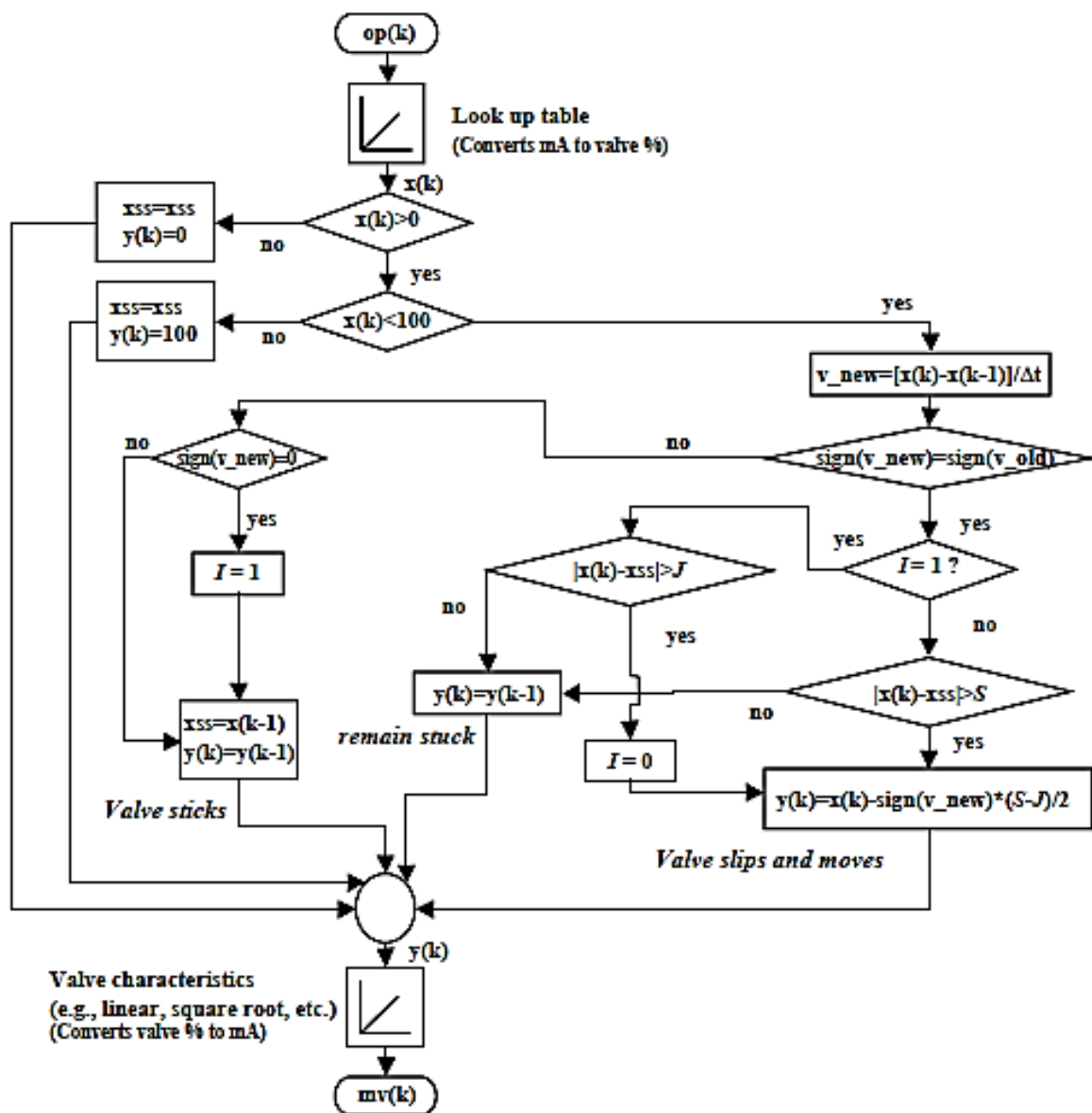


Fig. 9. Signal and logic flow chart of Choudhury stiction model

Once the output is found, it is then converted back to a 4-20mA signal using a look-up table based on the valve characteristics such as a linear, equal percentage, or quick opening.

In this section, a simulink model is developed based on the Choudhury stiction data-driven model to obtain an open-loop response of the stiction model by considering sinusoidal controller output with a magnitude of 100. All the types of stiction and valve without stiction has been simulated for different values of 'S' and 'J'. When there is no stiction in the valve, the response of valve input to valve output gives a linear relationship with the stiction model output exactly tracking the valve input as observed from Figure 10. Response for different stiction conditions like deadband for S=15, J=0, no offset condition with S=J=15, undershoot for S=20, J=10, and overshoot for S=15 and J=20 are shown in Figure 10.

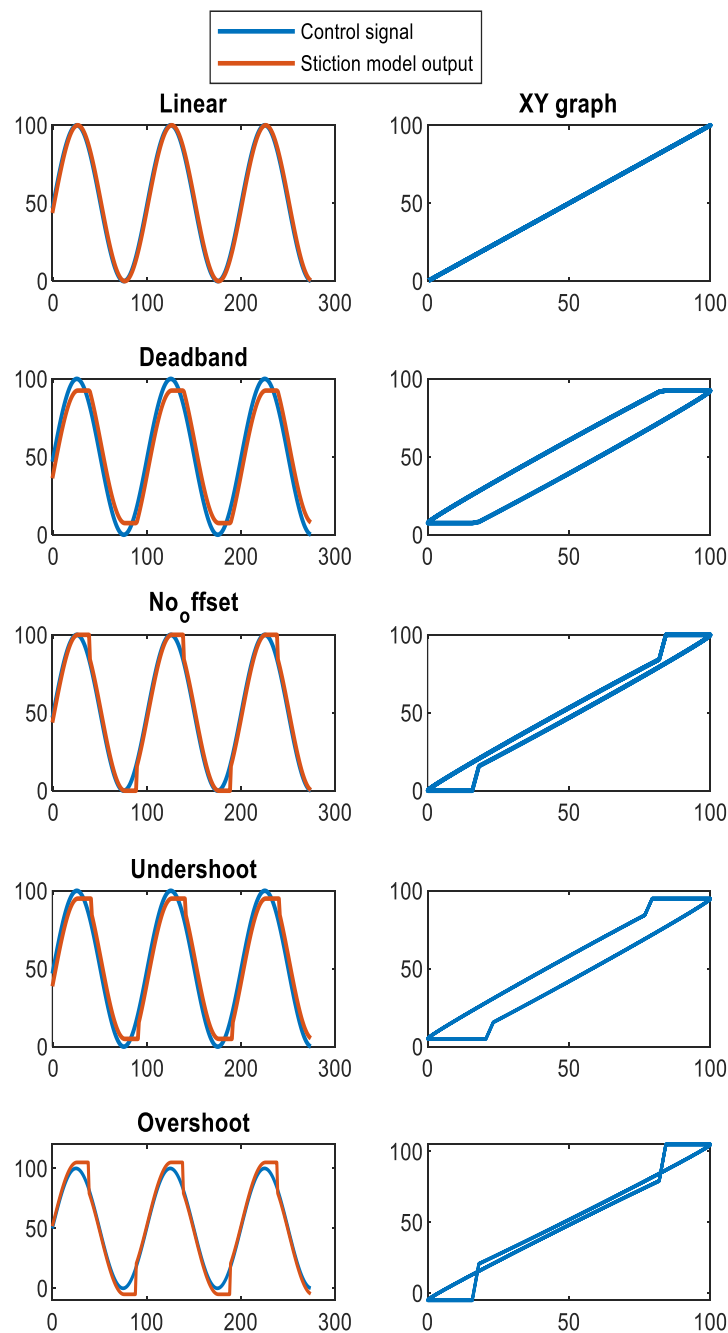


Fig. 10. Choudhury model open-loop output

5. Discussion

From the above-discussed articles, a comparison of different techniques used for the detection of valve clogging and diaphragm perforation is symbolized in the form of a chart in Figure 11 and Figure 12, respectively. Different techniques have been compared based on two performance indices, namely the detection rate, and false alarm rate. Time taken for detection of fault is also represented for some techniques available in the article. In some papers, details regarding false alarm rate and/or detection time are not available, hence the comparison is primarily given concerning the detection rate.

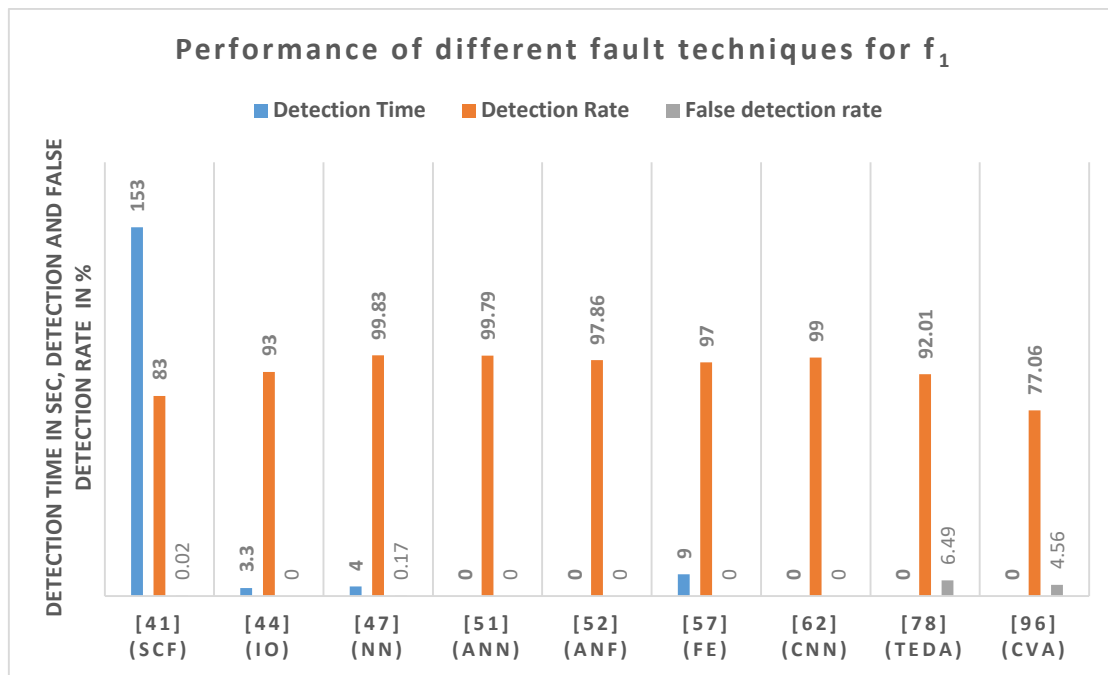


Fig. 11. Comparison of results obtained for the detection of f_1 fault. [SCF-Squared Coherency Function, IO- Interval Observer, NN-Neural Network, ANN-Artificial Neural Network, ANF-Adaptive Neuro-Fuzzy, FE-Feature Extraction, CNN- Chaotic Neural Network, TEDA-Typicality and Eccentricity Data Analytics, CVA Canonical Variate Analysis]

Figure 11 shows a chart representing the performance of different fault detection methods for valve clogging fault detection. From the chart, it is observed that Laurentys *et al.*, [47] have got a better detection rate of 99.83% with a false alarm rate of 0.17% for detection of valve clogging within 4 sec of fault occurrence. Subbaraj and Kannapiran [51] have achieved a detection rate of 99.79% which was a little less compared to Laurentys *et al.*, [47] with a zero false alarm rate and zero detection time. Hence algorithm used in Laurentys *et al.*, [47] gives better performance in terms of detection rate however a delay of 4 secs in fault detection. For diaphragm perforation fault, if only detection time and false alarm rate are considered then Przystała and Moczulsk [62] got a fault detection rate of 100% with 0.01% of false detection rate, Lingling Ma [96] attained a fault detection rate of 100% with 3.22% of false detection rate. In Laurentys *et al.*, [47], they have obtained a fault detection rate of 99.8%, a false alarm rate of 0.01%, and a detection time of 3 sec. Figure 12 shows a chart representing the performance of different fault detection methods for diaphragm perforation fault detection. When these articles were analyzed it is evident that, if the detection rate could be improved, then one has to give up in terms of increased false alarm rate and/or increased detection time.

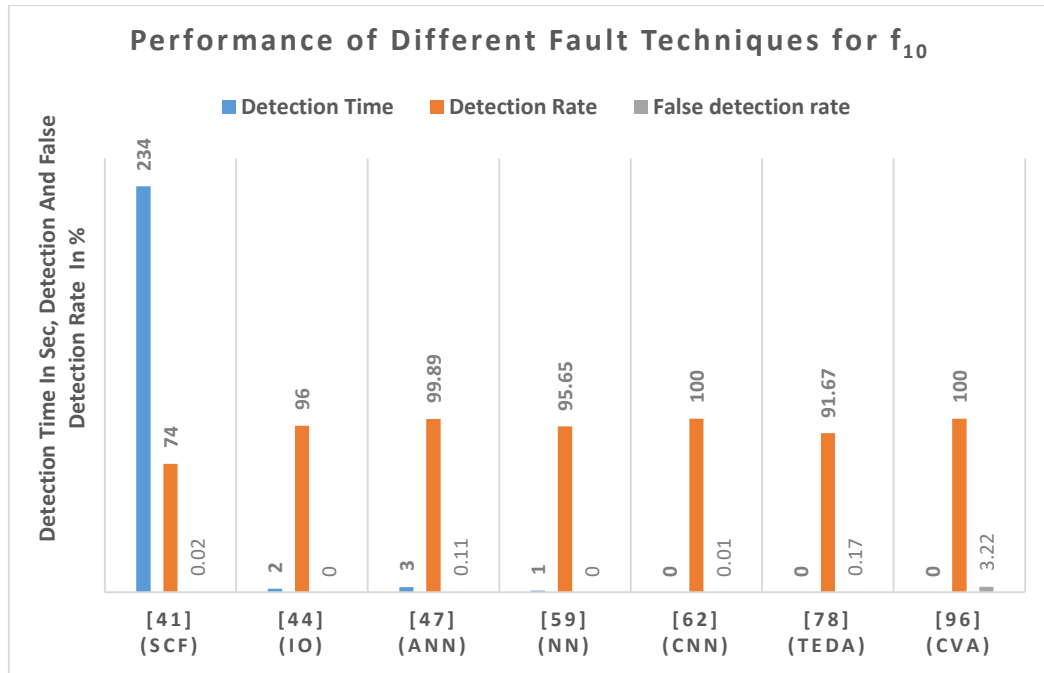


Fig. 12. Comparison of results obtained for detection of f_{10} fault

From the articles referred to in this paper, it is also observed that three faults namely, insufficient supply pressure, vent blockage, and diaphragm perforation faults have been detected using machine learning techniques in some papers. A comparison of different parameters of the techniques has been presented in Table 3. From the table if different techniques are compared based on computational accuracy, then the technique reported in Subbaraj and Kannapiran [52] has 100% accuracy besides computational time is 30.709 sec which is large comparatively. In Prabakaran *et al.*, [55], the computational time is 0.8761 sec which is less compared to all other methods with a computational accuracy of 99.01% and a classification error of 1.45%. As detection time is also an important parameter along with the detection rate, the technique discussed in Prabakaran *et al.*, [55] can be considered as better-performing amongst tabulated methods.

Table 3

Comparison of techniques used for the detection of insufficient supply pressure, vent blockage, and diaphragm perforation faults

Techniques	Artificial Neural Network [51]	Adaptive Neuro-Fuzzy [52]	Fuzzy Logic [53]	Radial Basis Network [54]	Self-Organizing Map [55]
No. Of training data	1000	1000	2500	1000	1500
No. of checking data	250	200	2500	1500	2500
Classification error	0.0017	0.00000469	1.33	1.2900	1.45
Computational time	2.7344 s	30.709 s	0.946163	3.2546785 s	0.8761 s
Computational accuracy	99.7%	100%	98.99%	98.09%	99.01%
Training error	0.0018	0.0000053	-	2.4447	0.00099567

From the aforementioned literature, it is observed that most researchers have reported the detection of only a few faults like abrupt faults, incipient faults, control valve faults, and stiction detection. The development of a technique to detect all 19 actuator faults is difficult as the behavior of faults and the rate at which they develop are not the same. Few researchers have developed a

technique for all actuator faults detection that has been compared in Table 4 based on the true detection rate (TDR) and false detection rate (FDR). Previdi and Perisini [41] have reported only results for abrupt faults. From tabulated values for Przystała, and Moczulsk [62] method, the technique can detect almost all the faults with good TDR but few faults f_4 , f_5 , and f_9 were detected with less TDR. In Bezerra *et al.*, [67], TDR for faults f_4 and f_{13} is very less, f_3 is detected with a 36% TDR, f_5 , f_6 , and f_{15} with a moderate TDR, and other faults were able to detect with TDR greater than 80%. Lingling *et al.*, [96] has reported a canonical variate method for the detection of faults with two methods Hotelling T2 and squared prediction error SPE for calculating detection rate and false detection. By considering both methods, a total of ten faults could detect, whereas other faults were not able to detect due to the fault pattern. Amongst all these methods, the technique used in Przystała and Moczulski [62] was able to detect more faults with a comparatively better TDR.

Table 4
 Comparison of techniques used for the detection of all pneumatic actuator faults

Faults	Previdi and persini [41]		Przystała, and Moczulsk [62]		Bezerra <i>et al.</i> , [67]		Lingling Ma [96]			
	TDR (%)	FDR (%)	TDR (%)	FDR (%)	TDR (%)	FDR (%)	TDR (%)		FDR (%)	
							T2	SPE	T2	SPE
F ₁	83	2	100	0	92.01	6.49	77.06	66.60	4.56	3.22
F ₂	81	2	100	0	83.33	1.20	100	80.74	4.44	3.22
F ₃	NA	NA	93	0	36.63	1.42	2.41	0	2.00	0.67
F ₄	NA	NA	55	1	0.00	1.47	1.27	0.38	2.00	0.67
F ₅	NA	NA	60	0	72.28	2.67	2.28	0	2.00	0.67
F ₆	NA	NA	96	0	73.27	2.67	2.34	0	2.00	0.67
F ₇	83	2	99	1	100	0.54	100	100	4.44	3.22
F ₈	83	2	NA	NA	93.33	0.29	2.41	0	2.00	0.67
F ₉	NA	NA	19	0	91.30	0.28	2.34	0	2.00	0.67
F ₁₀	74	2	100	1	91.67	0.17	59.44	100	4.44	3.22
F ₁₁	99	2	99	0	89.74	0.17	6.97	16.41	3.33	3.22
F ₁₂	66	2	95	0	93.02	0.16	1.71	8.56	2.00	0.67
F ₁₃	NA	NA	100	0	0.09	0.22	77.06	66.60	4.56	3.22
F ₁₄	81	2	NA	NA	80.76	1.52	2.41	0	2.00	0.67
F ₁₅	92	2	99	0	68.63	0.65	98.80	100	4.22	3.11
F ₁₆	NA	NA	99	0	83.52	0.60	53.74	71.10	4.11	3.00
F ₁₇	99	0	99	0	83.93	1.09	100	100	4.56	3.22
F ₁₈	93	2	100	0	93.65	1.15	76.68	62.99	4.56	2.44
F ₁₉	78	2	100	0	97.16	1.09	75.29	19.14	4.56	0.78

To initiate the stiction behavior in the valve model, an attempt is made to generate the stiction responses in simulation using a Choudhury data-driven model. Here a sinusoidal input with an amplitude of 100 is selected as a control signal to observe the stiction behavior with the model. Figure 10 shows the graphs obtained for different conditions of stiction like linear (without having stiction), pure dead band, no offset, undershoot, and overshoot. Each graph consists of the control signal and stiction model response plotted concerning time in the left part of the graph and their xy graph on right part of the graph. The change in graph for different combinations of S and J values is significant in xy graphs showing the relationship between the control signal and the model output.

6. Conclusion

Pneumatic control valves are an integral part of any flow process loop. Pneumatic control valves are used as actuators to vary the flow based on the control input. These valves are a combination of

the electromechanical structure, with a high rate of wear and tear. The predetermination of the life of the valve could provide potentially important information to the controller. Similarly, identification and isolation of the faults occurred would also lead to a substantial reduction in the loss. Considering the above-said importance an attempt is made in this paper to discuss an overview of the pneumatic actuator and its faults categorized based on the DAMADICS benchmark. Different techniques used for fault detection and isolation have been discussed and compared. Detailed discussion on pneumatic actuator faults based on four categories namely, control valve, servomotor, positioner, and general faults along with the classification of fault into abrupt and incipient based on their behavior and development time is discussed in this paper. Stiction is an incipient fault that is discussed as a combination of stuck and friction movement of the control valve. Detecting and diagnosing stiction is difficult due to its incipient behavior. Some techniques used for modeling and detection of stiction is also discussed in this paper. An attempt is made to generate the stiction responses in simulation using a Choudhury data-driven model. The change in graph for different combinations of S and J values is significant in xy graphs highlighted in Figure 10.

In most of the papers, abrupt fault detection was the main intension, whereas only a few articles have concentrated on detecting both abrupt and incipient faults. From Table 4 it is evident that most of the researchers have found difficulty in detecting f_4 and f_8 faults as these faults are indistinguishable faults. The technique used in [62] could detect more faults with a comparatively better detection ratio. Different techniques used for the detection of different faults have been compared majorly based on two performance indices, namely detection rate, and false alarm rate. Detection time is also used as another parameter as early detection of faults improves the performance of FDI methods. Detection rate, detection time, and false alarm rate are interdependent so that whenever one parameter is tried to improve, the other parameters were hampered. Thus, reasonably maintaining these parameters so that a nominal value of these indices would improve the efficiency of the technique.

From the discussion reported in this paper, it is clear that there are many types of fault detection or diagnosis technique which are discussed based on the type and application of these techniques. However, no technique is reported which can be used for all types of faults. It could be proposed that a multi-sensor fusion technique would be able to provide a platform to involve data from different sensors and fuse the sensor data to identify, classify, and isolate faults in pneumatic actuators.

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