Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal Vol. 7, No. 1, January 2025, pp: 231-242; eISSN: 2656-8632

RESEARCH ARTICLE OPEN ACCESS

Manuscript received November 5, 2024; Revised December 1, 2024; Accepted December 12, 2024; date of publication January 15, 2025
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v7i1.644

How to cite: Sayanti Chatterjee, Bhupesh Deka, Dipanwita Debnath, Sasmita Tripathy, and Bindu Agarwalla, "Robust Fault Detection of a Hybrid Control System Using Derivative Free Estimator and Reinforcement Learning Method", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 7, no. 1, pp. 231-242, January 2025.

Robust Fault Detection of a Hybrid Control System Using Derivative Free Estimator and Reinforcement Learning Method

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The authors express their heartfelt gratitude to the institutions VNR Vignana Jyothi Institute of Engineering & Technology, Koneru Lakshmaiah Education Foundation, Centurion University of Technology and Management, and Kalinga Institute of Industrial Technology for their unwavering support and resources during this research. Special thanks to Dr. Sayanti Chatterjee for her guidance as the corresponding author and for coordinating this collaborative effort.

ABSTRACT Fault detection in hybrid control systems (HCS) poses significant challenges due to dynamic variations in system dynamics caused by event-based inputs and the existence of unknown large process noise. A novel scheme for optimized robust fault detection of HCS has been proposed and projected here that can effectively handle dynamic system changes and process noise along with the fault detection while achieving high accuracy and reliability. The challenge with the HCS is the presence of a large process noises due to changing of state equations drastically with dynamical input making the fault detection a complex task. The derivative-free estimator minimizes process noise and provides reliable state estimation, while the Markov Decision Process (MDP) framework is employed to optimize fault detection. MDP has been chosen here due to its mathematical introspection for dynamic system's decision-making process when the results are random or under the control of a decision maker. The data generated by the derivative-free estimator is used to train this deep learning model. Simulation studies were conducted to evaluate the scheme's performance, and additional tests for convergence, optimization, and robustness were performed using MDP infused with adaptive estimators. The efficacy of the proposed estimators has been confirmed on a benchmark problems, namely the liquid level control system for an chemical stirred tank reactor (CSTR) model. Simulation studies has been employed to prove the efficacy of the proposed method. The proposed method achieved **98.6% fault detection accuracy** and a **12% mean error reduction** compared to existing techniques. It demonstrated robustness under varying noise levels, dynamic conditions and presence of external disturbances . The results confirm the method's effectiveness for robust and optimized fault detection in HCS, offering a **scalable, accurate, and noise-resilient solution** for real-world industrial systems

INDEX TERMS CSTR, Fault Detection, Hybrid System, Markov Decision Process, Q-Adaptive, Robustness Study.

I. INTRODUCTION

Robust Fault Detection in Hybrid Control Systems involves identifying and isolating faults in systems that integrate continuous dynamics (e.g., time-evolving system dynamics) with discrete logic or switching. This is a challenging task due to the interplay of continuous and discrete behaviours, presence of process and measurement noises noise, uncertainties, and potential nonlinearities. Fault detection in hybrid systems can be defined as a process of identifying abnormalities or malfunctions in systems that combine different components or operate across multiple modes. Smart Fault detection ensures the hybrid system maintains reliability, safety, and efficiency.

This work's primary focus is on "hybrid control systems," which are a unique class of complex systems that have two distinct subsystem types—continuous and logic-driven subsystems—that interact in real time to accomplish a shared objective or enhance performance and efficiency[1], [2].Discrete event dynamical systems (DEDS), which have drawn a lot of attention in the control literature, are the foundation of the hybrid systems structure. While a tutorial on modelling the dynamics of hybrid systems has been discussed in the work of [3], the lecture notes of John Lygeros [1] include examples of several HCS in this context.

The derivative free estimator is another feature of this publication. First order CDF has been selected as the main algorithm in this paper [4]. One of the derivative free estimator family's essential paradigms is CDF. These estimators are employed in adaptive learning and online parameter estimation, where models are changed instantly in response to fresh data. The primary benefit of employing a CDF-based estimator over the popular Derivative Free Filter (EKF) is that the latter has several known drawbacks, including complicated Jacobian computations and singularity issues. [5], [6] presented a linearisation procedure based on square root factorisation of the output covariance matrices.

In [7], estimators for time evolving nonlinear systems have been addressed where polynomial approximations has been used for linearization. In this work, two state estimators, namely: 1st order divided difference filter (DD1) and 2nd order divided difference filter (DD2) have been derived. It is shown that under certain assumptions the estimators perform better than estimators based on Taylor series approximations. A paper containing similar material has appeared in [8].

The paper of [4]is also consequential. In this work real-time and accurate estimators especially first order and 2nd order CDF have been developed and analyzed for nonlinear filtering problems based on the Gaussian distributions.

The paper of [5] has been presented a new algorithm based on numerically efficient central difference algorithm which is potentially suitable for on board implementation. The same group authors [5] also work on the adaptive version of it. The paper of [9] is also imperative in this area where adaptive divided difference filter has been successfully employed.

But the central theme of this thesis is the estimation of nonlinear hybrid system. Derivative free estimation for this type of system has been discussed in [10]. In this work, the performances in convergence, robustness and numerical stability of DDF, in state estimation of nonlinear systems are illustrated by an application to a three-tank system.

The other point of the novelty of this work is adaptive filter for hybrid systems. A very few papers are available in this domain. Adaptive filter has been first introduced by [11], followed by [12] . The paper authors[12], [13] deals with an adaptive nonlinear model estimator in cases of mismatch modeling, presence of perturbations and/or parameter variations for various applications. The adaptive estimator for hybrid control systems have been addressed in [13], [14], [15]

Another aspect of this work is intelligent fault recognition [16], [17]In this work the fault detection framework has been investigated by using deep reinforcement learning has been discussed in the paper [18], [19], [20]In the paper of [21], estimation performance of the novel hybrid estimator based on machine learning and extended Kalman filter has been detected. SVM infused with estimators has been found in [14], [22], but in this paper, MDP has been proposed for better accuracy which is basically a reinforcement learning.

A reinforcement learning based fault diagnosis for autoregressive-moving-average model has been first introduced by [18] . The fault detection using different filtering methods has been demonstrated in the literature for nonlinear systems [23], [24] which helps the current author to choose the central algorithm

The combination of estimator infused with different machine learning algorithm as discussed in prior literature[25], [26], [27]. SVM based fault detection has been also cited in this context [28]. The advanced version of machine learning, e.g. deep learning has been also demonstrated in this regard[29] . In this work, MDP has been trained with the data set derived from the estimator after filtering the process and measurement noises. As the process noise magnitude is unknown to the estimator, adaptive version has been taken into account for this work. The use of Markov decision process infused with central difference filter for fault detection of hybrid control system is the novelty of the work.

To evaluate the performance of these classifiers, the following metrics were employed:

1) Detection Accuracy (DA) and Detection time: The speed and accuracy to detect the fault
2) True Positive Rate (TPR): Correctness of fault detection
3) F1-score: The harmonic means of recall and precision.
4) Robustness study: The change in fault detection speed for different level of noises

The uniqueness of the current work as mentioned earlier is to detect the fault using hybrid reinforcement fault detection i.e. Markov Decision Process for hybrid control system. MDP which has been elucidated here is a combination of supervised and reinforcement learning. Derivative free 1st order central difference estimator has been successfully implemented to minimize the noises. The primary benefits of employing this kind of estimate scheme are: the linearization procedure is more accurate than the linearization technique used for EKF; ii. neither the Jacobian nor the Hessian matrix needs to be constructed.

The robustness study of the fault detection has been done for different process noise covariances and injecting the external disturbances. This chemical starred tank which has been elected to study the efficacy of the proposed method has been taken from the literature [14], [30], [31]. In the paper of the current author , the fault detection of same system has been introduced, but machine learning has not been addressed therein. Fault detection of liquid level controller using machine learning technologies have been discussed in paper [32] but hybridness of the plant has not been considered.

A comparative study of various machine learning algorithms to estimate liquid level has been illustrated in literature [32], [33]. The faults considered here are leakage fault [34], sudden change inflow and external disturbance.

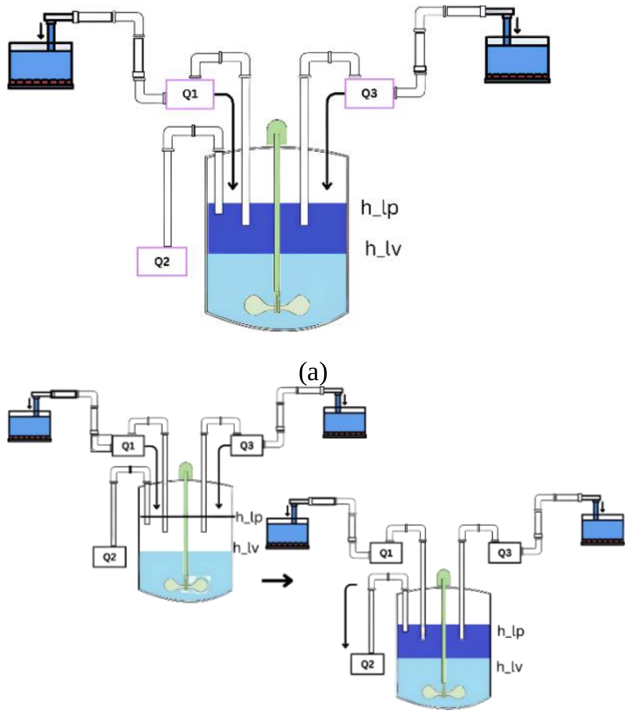
According to the literature review, there is a research gap because nonlinear hybrid control systems with process noise that the estimator is unaware of lack reliable and accurate fault identification. The current work aims to obviate the drawbacks of HCS and get a faster detection of fault with lesser latency and developed precision and accuracy. The main contribution of the present worker can be penned as:

1) Faster detection of fault with lesser latency and developed precision and accuracy using MDP based machine learning as it gives a mathematical introspection for dynamical systems when the outcomes are random and controlled by a decision maker. In the previous work, MDP has not been employed in such situation.
2) The primary drawback of HCS, is that the process noise quite high because of the estimator and truth model mismatch, which results in an incorrect fault detection. By using Q-adaptation, an adaptive estimator can avoid this disadvantage. Though the Q-adaptive derivative free estimator was proposed for NLHS in the current author's work, machine learning was not employed therein.
3) This work suggests combining the two aforementioned techniques, which are more effective and efficient for fault identification when there are significant noises and external disturbances present.
4) In this case, the effectiveness has been demonstrated using a chemical stirred reactor.

The remaining area of this work comprises of problem formulation, Algorithm for fault detection followed by problem solution and conclusion.

II. SYSTEM DESCRIPTION

In order to illustrate the newly developed idea of the suggested estimating and fault detection technique, the benchmark test problem of the chemical stirred tank reactor (CSTR) is examined in this section. This issue was drawn from the literature [14], [31]. Three control valves regulate the level of a fluid in a tank that makes up the system seen in FIGURE 1 (a). As illustrated in FIGURE 1, each valve opens or closes in accordance with the predetermined thresholds (h_lv and h_lp). Under adiabatic circumstances, a thermal power source heats the fluid in the tank uniformly. The diagram which has been chosen here the benchmark problem diagram. The same diagram has been used in the other work[14], [31]. The hybridness of the diagram is also describe in 1.b. When the water level is above the threshold level(h_lv) output valve remains closed but the inflow continues. Similarly, when the water level crosses the upper threshold(h_lp) the water starts to flow through the outlet. The FIGURE 1.b. shows the hybridness



(b)

FIGURE 1. Hybridness of the liquid level of CSTR based on the threshold value(mode) a. Schematic diagram of CSTR (Hybrid control system), b. Schematic Flow diagram according to mode change

A. PLANT MATHEMATICAL MODELLING

The following non-linear difference equations, which are derived from the mass and energy conservation rules, can be used to describe the state equations once the system dynamics have been discretized and other simplifying physical assumptions have been made. The fluid level is the first state (x_1) and temperature the 2nd state (x_2). Q_1 and Q_3 are designated as rate of flow through inlet valves whereas Q_2 is considered as the flowrate through outlet valve.. V_m is the assigned inlet fluid temperature, T^s is the time step, and w_k and v_k are the process noises and the measurement noises respectively. The mathematical equations e.g. (1) and (2). depicts the system dynamics and measurement respectively. The nomenclature has been given down.[30], [31]

$$\boldsymbol{\dot{x}_1 = T^S[\alpha_1 Q_1 + \alpha_3 Q_3 - \alpha_2 Q_2 + w_1]} \tag{1}$$

$$\dot{x}_2 = T^S/\dot{x}_1 * [\alpha_1 Q_1 + \alpha_3 Q_3 - \alpha_2 Q_2 + w_2 - (Vm + x_2)] \tag{2}$$

In Eq. (1) and Eq. (2) [31], x_1 is the level of the liquid column where as x_2 is temperature of the fluid w_1 and w_2 are process noises statistics with noise covariances Q.

$$y = C * \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + v_1, \textit{ where } C=[0\ 1] \tag{3}$$

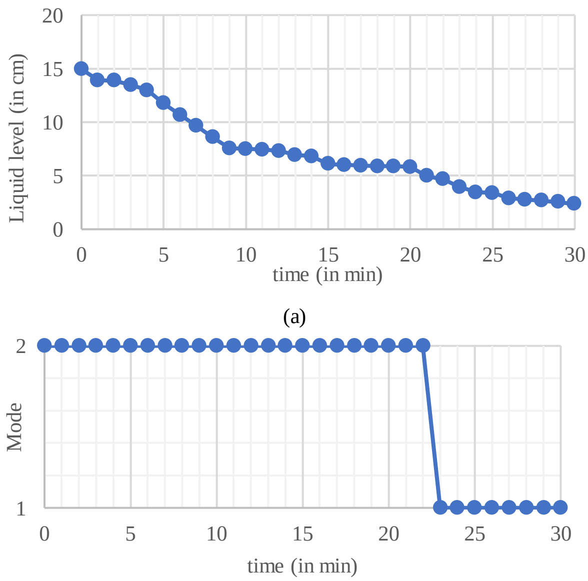
From Eq. (3)[31] it can be implied that **the CSTR temperature** has been measured as the **system output** where the values of the other plant parameters are given in the following table, i.e. TABLE 1.

TABLE1
Value of parameters of liquid level control system

Sl. No.	Name of the parameter	Value of the parameter
1.	inflow (q_1)	1l/m
2.	inflow (q_3)	3l/m
3.	outflow (q_2)	2.5 m/h
4.	inflow temperature (v_m)	15 degree cg.
5.	threshold height_lower (*h_lv*)	4 m
6.	threshold height_upper (*h_lp*)	10m
5	sample time (t^s)	0.01

B. MODE DESCRIPTION

A Continuous Stirred Tank Reactor (CSTR) operates as a **hybrid Control system** as the continuous aspect arises from the chemical reaction processes governed by differential equations, such as changes in concentration, temperature, and flow rates. The discrete nature emerges from events like switching control modes, valve operations, or system shutdowns, which cause abrupt state transitions. Depending upon the liquid level and water flow and valve operations, two modes can be described as in Eq. (4) to Eq. (5) [14], [31].



(b)

FIGURE 2 Change in mode and liquid level with respect to time a. **The time evolving measurement b. change in mode**

Mode I: Water level is below than lower threshold height or (h_lv< liquid-level<h_lp):

$$\boldsymbol{\alpha_1} = \boldsymbol{\alpha_3} = 1; \boldsymbol{\alpha_2} = 0 \tag{4}$$

Mode II: Water level is more than higher threshold height or (h_lp< liquid-level<h_lv):

$$\boldsymbol{\alpha_1} = \boldsymbol{\alpha_3} = 0; \boldsymbol{\alpha_2} = 1 \tag{5}$$

Response of liquid level control system under different conditions. In this section, the hybrid behaviour of liquid level control systems has been studied under different conditions. Validation has been done here through simulation studies. For this bench mark problem, the initial condition of liquid level has been assumed=15cm; and the tank temperature is 10 degree Celsius. Covariances of noise characteristics given in Eq.(6)[31] can be defined as :

$$Q = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.1 \end{bmatrix} \text{unit}^2 \quad R = \begin{bmatrix} 0.16 & 0 \\ 0 & 0.05 \end{bmatrix} \text{unit}^2 \tag{6}$$

In this scenario (FIGURE 2), CSTR can be considered as a hybrid control system with nonlinearity. The time evolving measurement is known as state as well as the event based logic are known as mode. The same nomenclature has been used in rest of the work.

C. FAULT MODEL

As discussed earlier, the proposed approach was validated liquid-level control system of a chemical stirred tank reactor (CSTR) model. Two types of fault model have been defined here to proof the efficacy of the method. They are namely leakage fault and sudden change in inflow. The fault equations have been illustrated by the given equations. Eq. (7) [14] describes the liquid leakage of valve 1 which can can be defined as

$$\boldsymbol{Qleak = a_f r_f^2 \pi \sqrt{2gx_1}} \tag{7}$$

where, a_f= leakage coefficient=0.4; r_f= radius of the leakage. The leakage in the chemical stirred tank results in a continuous outflow through the leak. The leakage flow depends on the radius of the leakage and a flow coefficient. The flow coefficient is a function of the fluid density and temperature. But for simplicity, here it has been considered as constant.

The other fault as in Eq. (8) [14] which is present in this work, is the sudden change due to improperness in valve activity or sudden shutdown of the inlet valve. Sudden change in flowrate through inlet1 (δ_f in percentage) has been given in Eq. (8) [14]. The inlet flow under fault condition becomes Q_{1f} which can be shown here:

$$Q_{1f}=\delta_f Q_1/100 \tag{8}$$

III. FAULT DETECTION ALGORITHM

For identifying faults, the commonly utilized method is based on residuals. The introduction of unforeseen noises alters the statistical properties of the innovation sequence or the residual sequence. The term "innovation" typically refers to the discrepancy between a measurement and its associated prior estimate. In contrast, the difference between a measurement and its corresponding posterior estimate is referred to as the residual.

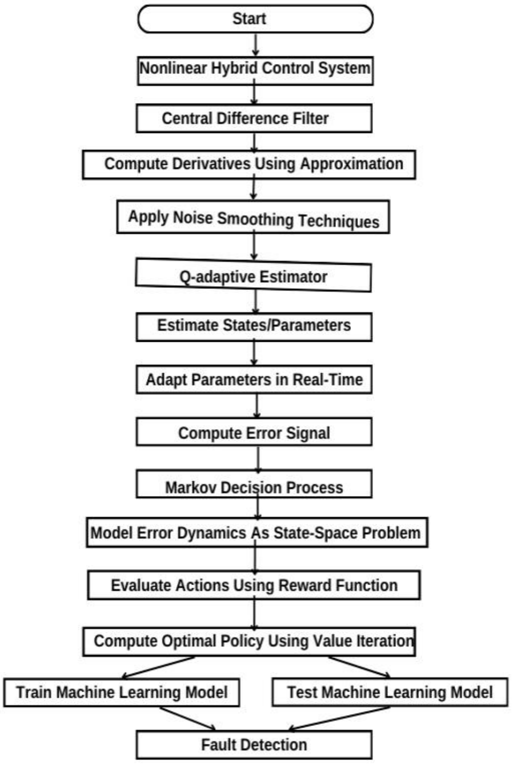


FIGURE.3. Flowchart for fault detection

The steps for fault detection have been described here in a flowchart in FIGURE 3. Measurement of hybrid structures are considered as the input of the estimator. These data are used to train the Markov Decision model.

A. Q ADAPTIVE DERIVATIVE FREE ESTIMATOR

In this work, Q-Adaptive versions of, self-switched 1st order central difference filter infused with reinforcement learning have been proposed and characterized in this paper. The detailed algorithm has been framed, only for one mode, i.e. basic nonlinear structure of estimator [5]has been depicted here (ALGORITHM 1). The state equation Eq. (9)[5], [6] and the output equation Eq. (10) [5], [6] of any plant in discrete domain are,

$$x_k = f(x_{k-1}) + u_k + w_k \tag{9}$$

$$y_k = g(x_k) + v_k \tag{10}$$

where $x_k \in \Re^{n_1}$ is a state vector of n_1 dimension, $u_k \in \Re^{n_2}$ is the known input vector of n_2 dimension. $f(.), g(.)$: vector function to map the state and measurement equations respectively as shown in aforementioned equations. The measurement is assumed to be a n_3 dimensional vextor written as $y_k \in \Re^{n_3}$. The zero mean noise sequences $w_k \in \Re^{n_1}$ and $v_k \in \Re^{n_3}$ denote respectively the process noise sequence with covariance $Q_k \in \Re^{n_1 \times n_1}$ and measurement noise sequence with covariance$R_k \in \Re^{n_3 \times n_3}$. $\hat{\boldsymbol{x}}_k$ and $\hat{\boldsymbol{y}}_k$ are chosen as estimated states and measurement. $\overline{x_k}$ and $\overline{y}_k$are elected as the apriori estimated states and measurements respectively whereas. P_k is advocated the error covariances.

ALGORITHM 1. Estimation using Derivative Free Estimator

Step 1: Initialization of P_0(state error covariance) and estimated state $\hat{x}_0$.

Step 2: Estimated state Propagation as given in Eq. (11) [5]

$$\bar{x}_{k+1} = \frac{1}{2}\sum_{p=1}^{n_1}\{f(\hat{x}_k + \hat{s}_{x,p}) + f(\hat{x}_k - \hat{s}_{x,p})\} \tag{11}$$

where $\hat{s}_{x,p} \in \Re^{n_1}$: p^{th} column of the square Cholesky factors $\hat{S}_x \in \Re^{n_1 \times n_1}$of $\hat{P}_k$ given by $\hat{P}_k = \hat{S}_x \hat{S}_{x_1}^T$.

Step 3: Apriori error covariance Calculation has been discussed in Eq. (12), Eq. (13)[4]**.**

$$S_{x\hat{x}}^{(1)}(k+1) = \frac{1}{2}\left(f_i(\hat{x}_k + \hat{s}_{x,p}) - f_i(\hat{x}_k - \hat{s}_{x,p})\right) \tag{12}$$

$$\bar{P}_{k+1} = S_{x\hat{x}}^{(1)}(k+1) S_{x\hat{x}}^{(1)}(k+1)' + Q_{filter} \tag{13}$$

Q_{filter} is the process noise covariance matrix used in the estimator in Eq.(12) [4]

$$\bar{P}_{k+1} = \bar{S}_x(k+1)\ \bar{S}_x^T(k+1) \tag{14}$$

As in Eq. (11-13) [4], p^{th} column is used to calculate of the square Cholesky factor $\bar{S}_x(k+1)$ as $\bar{s}_{x,p}$ The updation of error covariance has been demonstrated in Eq. (14) [4] and a time updated estimate of the output as in Eq. (15) [4].

$$\bar{y}_{k+1} = \frac{1}{2h^2}\sum_{p=1}^{n_1}\{g(\bar{x}_{l+1} + h\bar{s}_{x,p}) + g(\bar{x}_{l+1} - h\bar{s}_{x,p})\} \tag{15}$$

Step 4: Innovation Covariance Proliferation

$$S_{y\bar{x}}^{(1)}(k+1) = \left\{\frac{1}{2}\left(g_i(\bar{x}_{k+1} + \bar{s}_{x,p}) - g_i(\bar{x}_{k+1} - \bar{s}_{x,p})\right)\right\} \tag{16}$$

$$P_{k+1}^{y} = S_{y\bar{x}}^{(1)}(k+1) S_{y\bar{x}}^{(1)}(k+1)' + R_{filter} \tag{17}$$

In step 4, Eq. (16) [4] gives the process of the updating the covariances which in turn update the posteriori measurement update as in Eq. (17,18) [4]. Here,R_{filter} is the measurement noise covariance matrix used in the filter.

$$P_{k+1}^{xy} = \bar{S}_x^T(k+1)\left[S_{y\bar{x}}^{(1)}(k+1)\right]^T \tag{18}$$

The Kalman gain is given by Eq. (19) [5] which is further used to update the state equation and error value as shown in Eq.(20,21)[5], where K_k can be considered as Central difference filter gain without the noise adaption.

$$K_{k+1} = P_{k+1}^{xy}\left(P_{k+1}^{y}\right)^{-1} \tag{19}$$

$$\hat{x}_{k+1} = \bar{x}_{k+1} + \delta x_{k+1} \tag{20}$$

$$\delta x_{k+1} = K_{k+1}(y_{k+1} - \bar{y}_{k+1}) \tag{21}$$

The estimate the measurement as and the error covariance based on the apriori value and the calculated filter gain using Eq. (22), Eq. (23 [5], [6]) :

$$\hat{P}_{k+1} = \bar{P}_{k+1} - K_{k+1} P_{k+1}^{y} K_{k+1}^T \tag{22}$$

$$\hat{y}_{k+1} = g(\hat{x}_{k+1}) \tag{23}$$

Step 5: Q Adaptation Algorithm [11].

When process noise is unknown and measurement noise is known to the estimator, the following modifications are done. The modified process equation or noise updation has been discuses in Eq. (24) Eq. (25) [11].

$$res_k = y_{k+1} - \hat{y}_{k+1} \tag{24}$$

The covariances of the noise estimation has bee discussed in Eq. (25) [11].

$$C_v = \frac{1}{Ws} \sum_{i=k-k_w+1}^{k} (res_i)(res_i)^T \tag{25}$$

Ws is the window size. Estimate the diagonal elements of Q_{filter} as in Eq. (26) [11] where the adaptive coefficient δ has been defined in Eq. (27) [11].

$$\boldsymbol{Q_{filter} = Q_{filter}\sqrt{\delta}} \tag{26}$$

$$\textbf{where} \quad \delta = \frac{trace(C_v - R_{filter})}{trace(S_{y\hat{x}}^{(1)}(k+1) P_{k+1}^{xy} S_{y\hat{x}}^{(1)}(k+1)')} \tag{27}$$

A. *REINFORCEMENT LEARNING METHOD ALGORITHM*

Reinforcement Learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment, aiming to maximize cumulative rewards over time. Unlike supervised learning, where a model learns from labeled data, RL involves learning from the consequences of actions, through trial and error, to find the optimal policy for a given task.

B. *MARKOV DECISION PROCESS ALGORITHM*

MDPs are versatile and powerful, making them essential in sequential decision-making. If the system's fault dynamics (states, transitions, probabilities, and rewards) are well-understood and can be modeled mathematically, MDPs provide a structured approach. Fault detection systems often have predefined states (e.g., healthy, warning, failure), making MDPs a natural fit. MDPs allow precise modeling of the trade-offs between detecting faults early and the costs of false positives or maintenance actions. The core working model that administrates Markov decision processes is based on the Bellman Equation. The key features of the Bellman Equations are:

1) ***States (S):*** This is a precise outline of the environment that contains all the relevant information, works as an agent.
2) ***Actions (A):*** An agent made path which leads to state transition.
3) ***Transition Probability (P):*** The probability P(s′|s,a) of transitioning from one state to another state
4) ***Reward (R):*** Positive scalar feedback after the agent's action.
5) ***Policy (π):*** A transitional action strategy.
6) ***Discount factor(γ):*** Determines the future reward
7) **Bellman Equation**

Based on this features, the Bellman's equation is characterized by the following value function as in Eq. (28)[13].

$$V\pi(s) = \sum A\pi(A \mid s)\sum s'P(s' \mid s, A)[R(s,a,s') + \gamma V\pi(s')]V^{\{\pi\}(s)} \tag{28}$$

The detail steps of MDP have been discussed in the flowchart in given FIGURE 4, where the policy of the fault detection decision has been calculated using Bellman's equation.

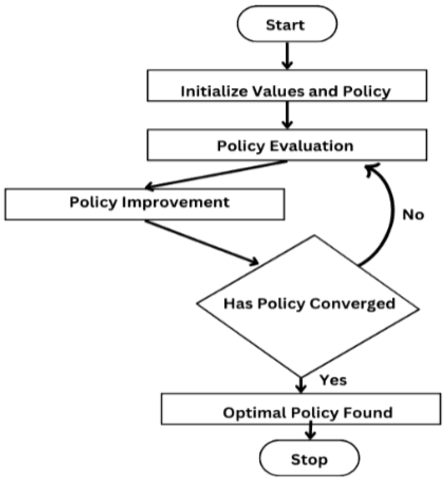


FIGURE 4: Flow chart of Markov Decision Process

IV. FINDINGS AND ANALYSIS

The mathematical modeling related to this case study has also been discussed in previous section. The same model has been reviewed here to achieve the objectives of the work. In the first case study, the initial condition has been assumed as: liquid level is x_1=15 cm; and temperature is x_2=10 degree Centigrade. The process noise covariances and measurement noise covariances are given below [15]:

$$Q = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.01 \end{bmatrix} \text{cm}^2 \quad R = \begin{bmatrix} 0.16 & 0 \\ 0 & 0.05 \end{bmatrix} \text{cm}^2$$

In this case study mode changes occur and the plant behaves like a nonlinear hybrid plant. The initial condition of the estimator is assumed to be [0 0] unit. No of Monte Carlo run is 1000. The liquid level has been considered as output. From the FIGURE 5, it is presumed t that in absence of any fault, the adaptive derivative free estimators provides satisfactory results.

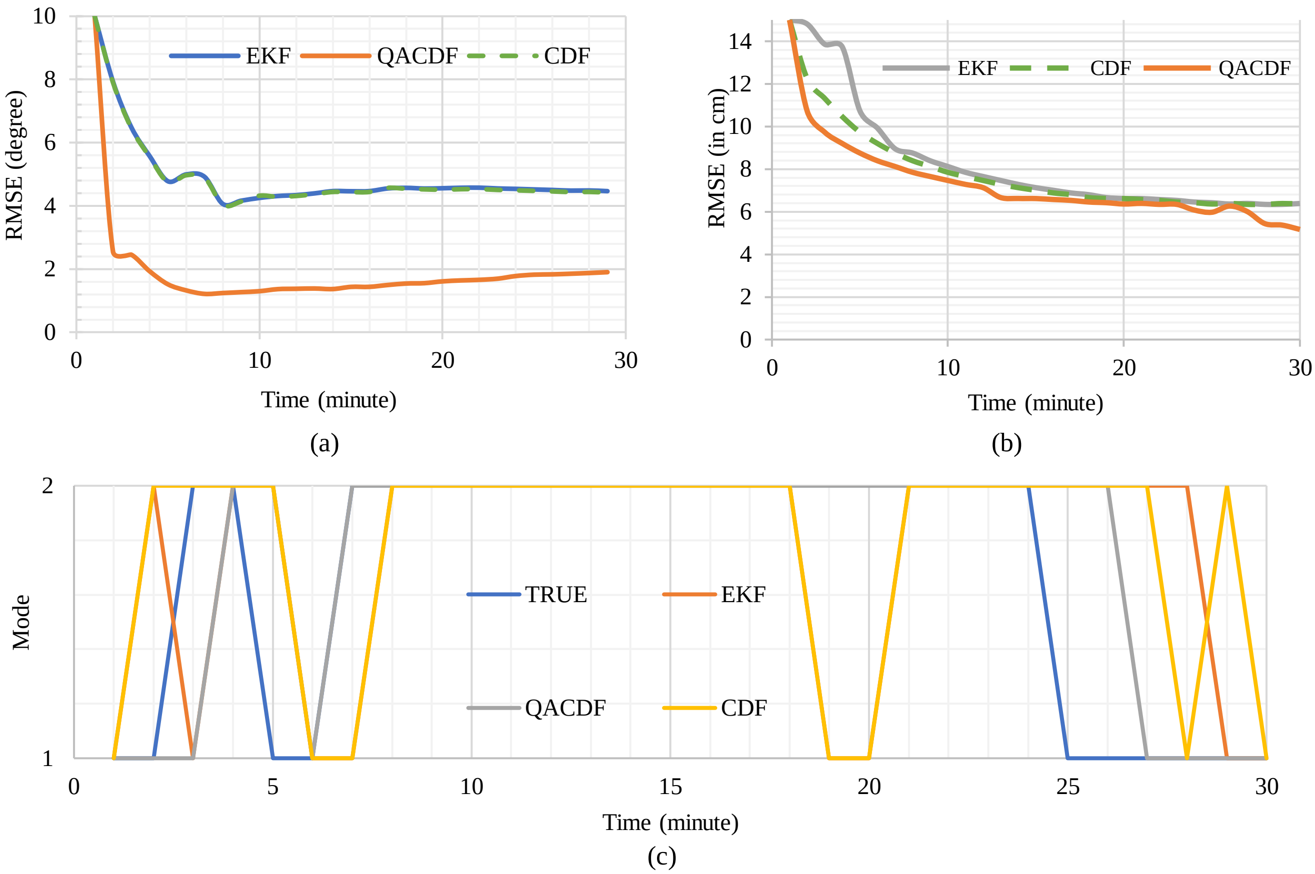


FIGURE 5: The estimation study using different estimator paradigm Root mean Square Error of (a) state2 (b) state1 (c) mode

TABLE 2
Speed of fault detection

Type of fault	Only CDF (**min.)**	SVM (min.)	Only MDP (min.)	ACDF+MDP (min.)
Leakage Fault	15	28	20	19
Sudden inflow	15	24	19	18

TABLE 3
Accuracy of fault detection

Type of fault	Only CDF (%)	SVM (%)	Only MDP (%)	ACDF+MDP (%)
Leakage Fault	84.94	92.13	94.23	97.65
Sudden inflow	88.92	93.02	94.39	98.17

TABLE 4
True positive rate of fault detection comparison

Type of fault	Only CDF (%)	SVM (%)	Only MDP (%)	ACDF+MDP (%)
Leakage Fault	0.78	0.88	0.92	98.65
Sudden inflow	0.86	0.92	0.94	98.17

TABLE 5
F1 score of fault detection comparison

Type of fault	Only CDF (%)	SVM (%)	Only MDP (%)	ACDF+MDP (%)
Leakage Fault	81.65	93.65	95.65	97.65
Sudden inflow	88.17	95.17	97.17	98.17

A. FAULT DETECTION USING MDP

As discussed earlier, fault detection is done here using MDP. Four parameters have been checked to show the optimization and efficiency of the proposed methods. The four parameters can be jotted down as speed of fault, detection, positive rate, and accuracy. Tables shows that MDP with ACDF gives better result with less latency. TABLE 2 to TABLE 5 proves that the estimator infused MDP gives better results with respect to other parameters. The same results can be obtained using different process noise covariances as process mismatch causes the maximum amount noises. FIGURE 6 to FIGURE 9 shows the comparison of different methods to prove the efficacy of the proposed method in the presence of different noise levels and presence of Leakage fault at 50 minute the comparison has been illustrated using the plots. The four parameters have been nominated here to prove the efficiency of the proposed methods. The parameters are namely Detection accuracy (ii) Detection speed, (iii)True positive rate and (iv) F1score.

The same results can be also obtained from the other fault (sudden change in inflow also). For all the studies process noise covariances (Q) are taken same as mentioned above. The process noise covariances and measurement noise covariances are given below [15]. It is assume the value of process noise covariances (Q) are given here. The value of the matrix has been varied to advocate the efficacy of the proposed method.

$$Q = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.01 \end{bmatrix} \text{cm}^2$$

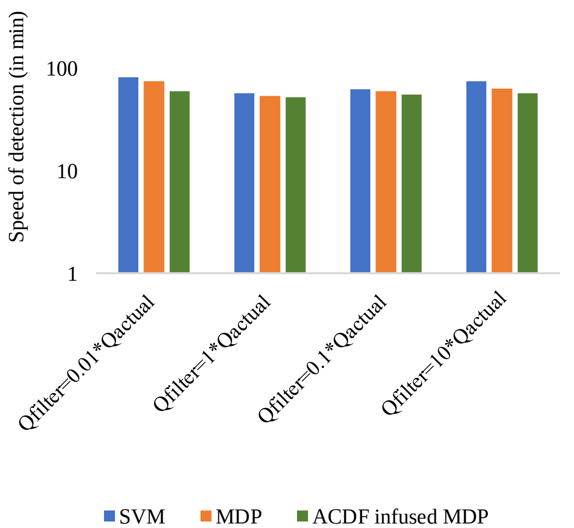


FIGURE 6: Comparison of Detection time

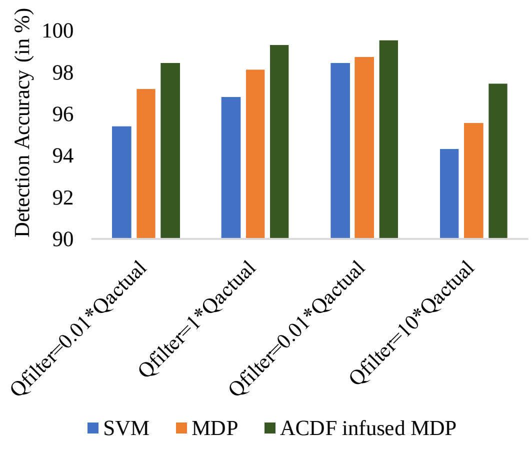


FIGURE 7: Comparison of Detection accuracy

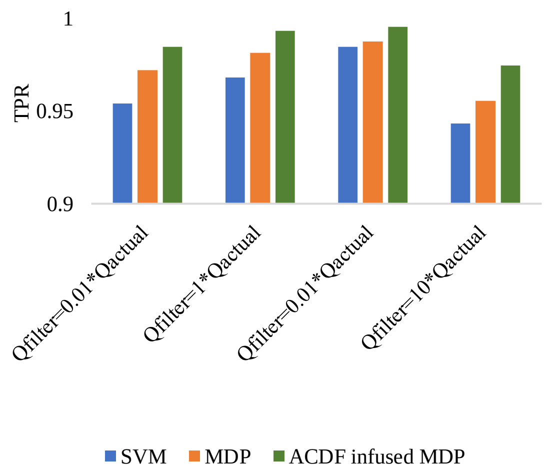


FIGURE 8: Comparison of True Positive Rate

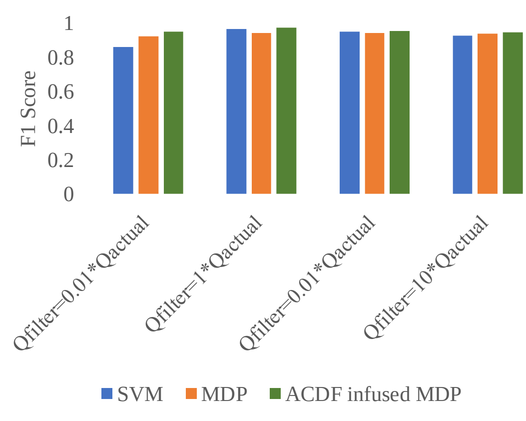


FIGURE 9: Comparison of F1-score

B. ROBUSTNESS STUDY

This section deals with the speed of fault detection using with different noise covariances and different windows using adaptive central difference filter for leakage fault. TABLE 6 exemplifies the robustness study in term of fault detection speed when noises are unknown to the filter. It is assumed that actual process noise covariance is Q. TABLE

7 demonstrates the fault detection technique for different window sizes. Same results can be deduced for the other faults. The tables proves that the MDP with ACDF based fault detection is robust and gives better result. The table (TABLE 6 and TABLE 7) provides a comparison study of the mean values of RMSE of 1st state within time scale 30-50 sec using Q-adaptive based estimation for different window sizes and initial value of process noise covariance is 10 times of truth.

TABLE 6
Comparison of speed of fault detection (fault occurrence at 50 min)

Process noise covariance initialization	0.01*Q (min)	1*Q (min)	10*Q (min)	.01*Q (min)
ACDF+MDP	60	52	55	57
ACDF+SVM	75	53	58.25	63
Only MDP	82	55	62	75

TABLE 7
Comparison of speed of fault detection (fault occurrence at 50 min)

Window Size	5	10	15	20	25
ACDF+MDP	65	57	55	56	59
ACDF+SVM	68	60	58	59	68.5
Only MDP	74	65	60	52	75.2

In the last section the external input is added to the inflow. It is assumed that the external input is a sinusoidal extra input added to the main inflow. The new inflow equation as in Eq. 22 [14] can be rewritten as:

$$x_1(k+1) = x_1(k) + T^s(\alpha_1 Q_1 - \alpha_2 Q_2) + noises + D1\sin(0.5k) \tag{22}$$

Here *D1* is the disturbance covariance. TABLE 8 shows the efficiency of the newly proposed estimator infused machine learning technique for fault detection in presence of external disturbance. Here also, leakage fault has been addressed to show the usefulness in presence of different disturbances.

TABLE 8
The fault detection speed for different *D1* value.

Disturbance value	0	1	2	0.5
ACDF+MDP	52	57	62	56
ACDF+SVM	53	61	65	59
Only MDP	55	65	68	52

V. DISCUSSION

In this work, a Continuous Stirred Tank Reactor (CSTR) operates as a **hybrid system** due to its combination of continuous and discrete dynamics. The continuous aspect rises from the chemical reaction processes governed by differential equations, such as changes in concentration, temperature, and flow rates. The discrete nature emerges from events like switching control modes and valve operations These hybrid characteristics make fault detection challenging, as the system dynamics can change nonlinearly with discrete inputs by rising a huge amount of noises. Addressing these challenges requires robust models capable of handling both the continuous dynamics and discrete transitions inherent to hybrid systems.

TABLE 9
Comparison of fault detection methods

Method	Key Features	Strengths	Weaknesses
Traditional Method (Threshold based) [9]	Relies on predefined thresholds for system variables to detect faults.	Simple to implement; computationally inexpensive.	Ineffective in handling noise, nonlinearity, and dynamic transitions in hybrid systems.
Estimator Methods (e.g., Observer, Filter) [30], [31]	Uses state observers to estimate system dynamics and residuals for fault detection.	Provides accurate state estimation for linear systems; widely used in control systems.	Struggles with nonlinearities and large process noise; requires linearized system models.
Support Vector Machine (SVM)-Based Methods [28]	Machine learning model trained on labeled data to classify faults.	Effective for simple classification tasks; handles moderate levels of nonlinearity.	Requires labeled fault data; lacks adaptability to dynamic changes in hybrid systems.
Only Deep Learning-Based Fault Detection [20]	Leverages neural networks to detect faults based on large datasets.	Capable of handling complex nonlinearities and dynamics; scalable to high-dimensional data.	Requires significant data and training time; can lack interpretability.
Proposed MDP-infused Adaptive Estimator Based Method	Uses a Markov Decision Process with derivative-free estimators for fault detection.	Handles nonlinearity and noise robustly; optimizes fault detection actions using rewards and penalties.	Requires careful modeling of transition probabilities and reward functions; training can be resource-intensive.

TABLE 10
Quantitative comparison using results from literature

Study	Method	Accuracy (in %)	False Positives	Robustness to Noise	Adaptability
X. Chen, et.al. 2020 [23]	Kalman Filter-Based	89.2	Moderate	Low	Low
Q. Zhang, et.al. 2019 [24]	Particle Filter-Based	93.4	Low	High	Moderate
L.Hong, et.al. 2022 [28]	SVM-Based	90.5	Moderate	Moderate	Low
Gao et.al.2023 [29]	Deep Learning-Based	95.8	Low	Moderate	High
Chatterjee 2022 [22]	UKF infused with SVM	96.2	Low	Moderate	High
Proposed work	**MDP with Derivative-Free Estimators**		**Very Low**	**High**	**High**

In the first section of the work, the efficacy of adaptive derivative free estimator paradigm has been studied in presence of different process noises. The second section deals with the comparison of different parameters of fault detection. It shows that use of MDP for fault detection in nonlinear hybrid systems provides a robust framework to manage uncertainties and optimize detection strategies. The derivative free estimators minimize the calculation complexity and time, thus improving the fault detection speed. Combining MDP with techniques like adaptive derivative-free estimators enhances its capability to adapt to complex, dynamic systems.

A. COMPARISON WITH EXISTING WORK:

This section deals with the comparison of the current work with the existing method as well as the literature. A deep interpretation has been analysed in a tabular from (TABLE 9) between the benchmark schemes to show the implications of the projected methodology. methods A comparative analysis (TABLE 10) of the proposed MDP-based fault detection scheme against existing methods from the literature for fault detection in nonlinear hybrid systems helps the researchers to find out the rationale of choosing the methodology. From the both table it can be concluded that proposed method is better than the existing state of art methods in terms of accuracy, robustness adaptability etc. But only weakness of the proposed method is mathematical complexity and the proper design. From the above study, it can be concluded that the adaptive estimator infused MDP-based fault detection scheme outperforms traditional and contemporary methods in terms of accuracy, robustness, and adaptability. These advantages make it a compelling choice for complex industrial systems, such as the CSTR model, where dynamic changes and noise are prevalent.

B. WEAKNESS OF THE PROPOSED METHOD

The main weakness of this proposed scheme is to detect the fault is the dependency on accurate model representation. The scheme relies heavily on the accuracy of the derivative-free estimator and the Markov Decision Process (MDP) framework. But the use of adaptive filter can minimize this problem. Another weakness is the computational complexity. But it is worthy as the system gives highly satisfactory output.

C. IMPLICATIONS OF THE PROPOSED METHOD

The main implications of the proposed methods gives the enhanced fault detection accuracy. With a demonstrated fault detection accuracy of 98.6% and a 12% mean error reduction compared to existing techniques, the proposed scheme sets a new benchmark for hybrid control system fault detection, potentially driving improvements in system reliability and safety.

Another importance of this method is the robustness against noise and dynamic variations. The method's resilience to process noise, dynamic system changes, and external disturbances highlights its potential for deployment in noisy and highly variable industrial environments, ensuring stable operations under challenging conditions. Using the proposed method the researcher can employ it for hybrid control systems, promoting their broader adoption across industries.

D. FUTURE SCOPE

To begin with, the effectiveness of this method can be assessed in large-scale industrial settings, like multi-reactor networks or distributed processing systems. Furthermore, integrating real-time adaptive learning features would allow the model to manage unmodeled dynamics and unidentified faults more efficiently. Moreover, broadening the approach to support multiple fault situations and cascading failures would enhance its resilience. Lastly, the method could gain from hardware acceleration—for instance, utilizing GPUs or edge-computing devices—to maintain real-time performance in environments with limited resources.

VI. CONCLUSION

Detecting faults in hybrid control systems (HCS) remains a complex challenge due to dynamic variations and significant process noise. Thus the aim of this research work is to present a novel scheme for optimized robust fault detection in HCS using a derivative-free estimator and the Markov Decision Process (MDP) framework in the presence of unknown noise covariances as well as external disturbances. The proposed method effectively handles dynamic system changes and minimizes process noise, achieving high accuracy and reliability. Through simulation studies and additional tests on a chemical stirred tank reactor (CSTR) model, the approach demonstrated impressive results with an average fault detection accuracy of 98.6% and a 12% mean error reduction compared to existing techniques. Leakage fault and sudden changes in inflow has been considered to advocate novelty of the proposed method. Four parameters, namely accuracy, speed of fault detection, precision and true positive rate, have been evaluated to demonstrate the optimization and effectiveness of the suggested methods. The aforementioned tables for different faults indicate that MDP with ACDF produces superior results with reduced latency. The system's robustness under varying noise levels, estimation window and dynamic conditions like external disturbances has been demonstrated here using several case studies. The method further highlights its potential as a scalable, accurate, and noise-resilient solution for real-world industrial applications, significantly advancing the field of fault detection in HCS.

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