Active Fault-Tolerant Control Design for Actuator Fault Mitigation in Robotic Manipulators

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ABSTRACT This paper proposes an active fault-tolerant control (FTC) scheme for robotic manipulators subject to actuator faults. Its main objective is to mitigate actuator faults and maintain system performance and stability, even under faulty conditions. The proposed FTC design combines the robustness and finite time convergence of non-singular terminal synergetic control with the optimization properties of an interval type-2 fuzzy satin bowerbird algorithm. System stability is established via the Lyapunov stability criteria. An adaptive state-augmented extended Kalman filter is implemented as the fault detection and diagnosis (FDD) module, to provide the controller with necessary information about faults in real time. This FDD scheme is based on the simultaneous estimation of the faulty parameters and system states. The effectiveness of the proposed approach is assessed using a simulated two-degree-of-freedom robotic manipulator subject to various faulty scenarios.

INDEX TERMS Non-singular terminal synergetic control, adaptive augmented extended Kalman filter, Lyapunov stability, active fault-tolerant control, interval type-2 fuzzy system, robot manipulator.

I. INTRODUCTION

The increased complexities of modern industrial and automated systems, along with the wide usage of robotic systems, has led to a growing demand for their safe and accurate operation. This complexity has also increased the probability of faults occurring in robotic actuators and/or sensors. Conventional controllers may not be able to perform the desired tasks suitably in the presence of such faults. Hence, fault-tolerant control (FTC) has become an increasingly relevant topic in the last decade [1]. The objective of an FTC design is to maintain the desired performance and stability properties in the event of faults. FTC approaches can be classified into two categories: passive and active [2].

In the passive approach, robust control techniques are utilized to ensure that the control loop system remains insensitive to certain faults. For instance, a passive FTC scheme was proposed in [3] that employs a three-block controller to achieve perfect trajectory tracking in the presence of additive faults. However, as mentioned in the paper itself, the main drawback of that method is that it requires a large magnitude of control, and consumes more energy at times when faults are present. On the other hand, these types of controllers are only tolerant to a small set of predefined faults. Hence, in the event that a fault occurs that has not been predicted in advance, the controller may not be able to cope with this, which would lead to a performance degradation.

In active FTC (AFTC) [4], the controller is developed and modified such that it can handle a wide range of faults in sensors and/or actuators. For instance, a fault-tolerant backstepping control is proposed in [5] to deal with actuator faults based on nonlinear virtual control input. In the proposed design, the actuator faults and external disturbances are both modeled as additive terms and the FDD scheme is only able to estimate the time and total effect of the actuator faults, hence hampering its ability to properly isolate the faults. Additionally, the effect of the noise on the performance of the FDD module was not taken into consideration. A robust AFTC approach based on the proportional feedback control and a statistical regression observer-based FDD module for fault detection was proposed in [6]. The FDD scheme considered in [6] is based on a linear regression observer. Though this
method is not very complex computationally as compared to other FDD methods, one of its major problems is its reliance on the accuracy of the measurement data. This later is often affected by measurement noise. On the other hand, it is usually accurate within a small linear range for most of nonlinear systems. To overcome the problem of total loss of actuator in quadcopter UAVs, a robust adaptive sliding mode Thau observer is proposed in [7] to estimate the magnitudes of actuator faults, then a fault-tolerant control scheme is proposed based on the sliding mode control to maintain the performance of the system. The proposed observer is only able to diagnose the magnitude of the fault and based on this information a combination of FD and FTC is proposed. The proposed schemes are applied on linearized quadcopter without considering the effect of noises. Other recently published papers [8], [9] proposed active fault tolerant control schemes for robotic manipulators. A first-order sliding mode observer was implemented in [8] as the FDD system. This latter aimed at detecting and estimating the torque fault which was then passed to the kinematic controller to mitigate it. [9] proposed a self-tuning fuzzy PID-nonsingular fast terminal sliding mode control. It has been assumed that a FDD module provides the necessary information for the AFTC. The main drawback of these two papers is that none of them have considered the effects of process and measurement noises on the overall performance of the FDD and FTC modules. The noise can affect the accuracy of the FDD module thereby resulting in poor performance of the overall system. It can be concluded from these references that the fundamental component of an AFTC is the process of detecting and identifying faults via a fault detection and diagnosis (FDD) module [10]. This module should provide critical information about the fault to the controller, such as the fault location, size, and type. In the event that multiple faults occur simultaneously, the FDD module should be able to identify all of these and manage the previously mentioned information for each fault. Various FDD methods and approaches have been introduced in recent years, and these can be categorized into data-based and model-based methods [11].

The first category encompasses artificial intelligence-based approaches, such as those involving evolutionary algorithms [12], [13], neural networks [14], [15], fuzzy logic [16], and pattern recognition [17] and parity space-based approaches [18]. The second group monitors the observed variables and compares them with the estimated variables, providing a residual from this comparison [19]. The normal and fault-free condition should have a residual close to zero, and any miss-match between the observed and estimated signal causes vibrations and violations that can result from process and measurement noises, external disturbances, or faults. Therefore, the FDD module should be accurate and sensitive to faults, but at the same time not overly sensitive to noises and disturbances. These conditions are not satisfied by some previously introduced methods. For instance, an FDD approach based on an unknown input observer was presented in [8], which attempts to detect torque faults based on a sliding mode observer. As mentioned in that paper, the main drawback is a lack of robustness in the presence of process and measurement noise.

Model-based methods, relying on a dynamic model of the system, are more common, and provide significantly more reliable information. Among the various versions of the Kalman filter that have been introduced in previous studies, the extended Kalman filter (EKF) [20], unscented Kalman filter (UKF) [21], and square-root unscented Kalman filter (Sr-UKF) [22], [23] can be considered the most popular model-based methods, which generate residual signals of monitoring fault parameters in the presence of noise. For instance, [24] employed the EKF to detect sensor faults in an experimental interior permanent-magnet synchronous motor. In another study, the adaptive form of the UKF was adopted to detect the anomalies of continuous glucose monitoring (CGM) sensors [21]. Two types of sensor fault, drift- and pressure-induced, were targeted in that study. It can be observed that Kalman filters have a wide range of usage, in industrial bio-medical signal processing applications and beyond. Hence, in this study an adaptive EKF algorithm is proposed as the FDD module, which detects actuator faults using a simultaneous state and parameter estimation scheme. The proposed method is capable of providing the necessary information on faults in the presence of unknown and time-varying noise statistics. This information will be utilized in the FTC module to modify the controller to tolerate these faults.

Among the necessary conditions to be satisfied in industrial applications, robust behaviour against disturbances, fast response, and easy implementation can be considered as the most important features when comparing controllers. From this viewpoint, the sliding mode controller (SMC) is a suitable choice that satisfies all of these conditions [25], [26]. Various modified versions of this controller have been introduced to address some of the drawbacks of standard SMCs. For instance, [27] and [28] introduced an alternative non-singular terminal sliding surface, which avoids the singularity problem of the terminal sliding surface and also guarantees the finite-time convergence of the systems to the origin. A combination of artificial intelligence and an SMC has also been studied as a method to modify SMC performance [25]. Sliding-mode control based on an interval type-2 Takagi–Sugeno fuzzy system was introduced in [29], which attempts to address the problem of uncertain nonlinear systems. As a recent work in this filed with application to robotic manipulators, [30] proposed a non-singular terminal sliding mode control for a fusion reactor vacuum vessel assembly robot. These features have also persuaded researchers to apply sliding mode-based controllers to FTC systems [31], [32]. For instance, [33] introduced a combined scheme of a robust $H_{\infty}$ controller and sliding mode-based controller. In addition, [34] introduced an integral terminal sliding mode controller to deal with simultaneous actuator faults and actuator saturation limits in a quadrotor unmanned aerial vehicle. However, the main drawback of sliding mode-based controllers is the chattering phenomenon, which results in a large control
signal magnitudes owing to the mechanism of the controller. Various methods have been proposed to reduce the effect of this phenomenon, but these come at the cost of performance and robustness degradation [25], [35].

The main contributions of this paper are as follows:

- The integration of both FDD and FTC modules; whilst most works either deal with FTC design assuming the FDD system perfectly detected the faults or only consider and study FDD modules.
- The design of an adaptive augmented EKF (A-AEKF)-based FDD module that is capable of detecting, identifying, and isolating simultaneous actuator faults, even in the presence of process and measurement noises with unknown and time-varying statistics.
- The design of a non-singular terminal synergetic control (NTSC)-based FTC module, which guarantees the finite-time convergence of the system’s states to zero, while eliminating the singularity problem associated with the terminal version of this controller ( [36]) and ensuring a chattering-free response.
- The implementation of an interval type-2 fuzzy satin bowerbird optimization (IT2FSBO) approach, to enhance the performance of the controller by changing the basic optimization algorithm to an adaptive version.

This paper is organized as follows. The overall scheme of the proposed active FTC method is described in Section II. Here, the adaptive augmented EKF-based FDD module, fault-tolerant module, and interval type-2 fuzzy system are discussed. Computer simulation results illustrating the performance of the proposed approach using a two-degree-of-freedom (2-DoF) robot manipulator subject to various fault scenarios are presented in Section III. Finally, Section IV concludes this paper.

II. NON-SINGULAR TERMINAL SYNERGETIC FAULT-TOLERANT CONTROL

The overall scheme of the proposed active FTC approach is depicted in Fig. 1. First, the proposed A-AEKF algorithm detects and estimates potentially occurring actuator faults. In the fault-free case, the synergetic-based control law tuned by an intelligent fuzzy system will be utilized. In the event that a fault is detected, the reconfiguration mechanism will switch the controller over to the active fault-tolerant controller. This ensures that the controller is only adaptively changed when faults occur, saving computational time and costs.

Details about each component are provided in the following subsections.

A. FAULT DETECTION AND DIAGNOSIS METHODOLOGY

The proposed algorithm should be capable of correctly detecting the time, size, and location of a fault. For this purpose, an adaptive EKF is first introduced. Then, the model used to define the fault is presented and the decision-making procedure is discussed.

1) ADAPTIVE EXTENDED KALMAN FILTER

As previously mentioned, an EKF is proposed to estimate the states of the nonlinear system. This filter is a very common estimator, owing to its easy implementation, which employs the Jacobian matrix to linearize the system around its operating point [24]. The EKF is briefly summarized as follows:

Consider the following nonlinear system:

\[
\begin{align*}
\dot{x}(t) &= f(x(t), u(t)) + w(t) \\
y(t) &= h(x(t)) + v(t),
\end{align*}
\]

where the state vector, outputs, and controlled inputs are represented by \( x \in \mathbb{R}^n \), \( y \in \mathbb{R}^m \), and \( u \in \mathbb{R}^r \), respectively. The nonlinear functions \( f \) and \( h \) describe the dynamics of the system. Additive Gaussian white noises are denoted by \( w \sim N(0, Q) \) and \( v \sim N(0, R) \), which indicate that the noises have zero mean and covariance matrices \( Q \) and \( R \), respectively. The summarized EKF algorithm is presented in Algorithm 1. It should be noted that considering \( T_e \) as the sampling period, the values of the variables in the following algorithm are calculated at each sampling time \( k.T_e \). However, to prevent complexity in the notations and formulas, \( k.T_e \) is replaced by \( k \).

In Algorithm 1, \( \hat{x}_k^- \) is the \textit{a priori} estimate of the state, \( \tilde{x}_k \) represents the \textit{a posteriori} estimate based on the measurement of \( y_k \), and \( P_k^- \) and \( P_k \) represent the \textit{a propri} and \textit{a posteriori} error covariances, respectively. These error covariances are corrected and minimized at each sample time by calculating the Kalman gain as \( K_k \), using the Jacobian matrices of \( F_{k-1} \) and \( H_k \).

Among all the parameters of the EKF algorithm that must be set \textit{a priori}, including \( \tilde{x}_0 \), \( P_0 \), \( Q \), and \( R \), the process and the measurement covariance matrices have the most significant influence on the performance of the algorithm. Choosing \( R \) and/or \( Q \) matrices that are too small or large can lead to biased solutions or divergence. On the other hand, any mismatch between the real covariances that affecting the system and those assumed in the EKF algorithm can have a serious impact on the performance of the EKF, and in some cases can lead to estimation divergence. Hence, in this study the noise covariances of the \( Q \) and \( R \) matrices are estimated using the adaptive EKF (A-EKF) algorithm.

To estimate the noise covariances of the dynamic model given in (1), two assumptions are adopted. First, it is assumed...
Algorithm 1 Extended Kalman Filter (EKF)

1: Initialization:
\[ \hat{x}_0 = E[x_0], \]
\[ P_0^+ = E \left[ (x_0 - \hat{x}_0) (x_0 - \hat{x}_0)^T \right] \]

2: for all samples do
3: Time Updating:
\[ \hat{x}_{k^-} = f(\hat{x}_{k-1}, u_{k-1}) \]
\[ F_{k-1} = \frac{\partial f(\hat{x}, u)}{\partial x} |_{x=\hat{x}_{k-1}, u=u_{k-1}} \]
\[ P_{k^-} = F_{k-1} P_{k-1}^{+} F_{k-1}^T + Q_{k-1} \]

4: Measurement Update:
\[ H_k = \frac{\partial h(\hat{x})}{\partial x} |_{x=\hat{x}_k} \]
\[ K_k = P_{k^-} H_k^T \left( H_k P_{k^-} H_k^T + R_k \right)^{-1} \]
\[ \hat{x}_k = \hat{x}_{k^-} + K_k (y_k - h(\hat{x}_{k^-})) \]
\[ P_k^+ = (I - K_k H_k) P_{k^-} \]

5: end for

that the noises have Gaussian distributions \( w \sim N(q, Q) \) and \( v \sim N(r, R) \), and second it is assumed that the noise distributions are uncorrelated. Thus, the estimated values of the means and covariances can be obtained by maximizing the a posteriori density function as follows:

\[
J^* = p[X(k), q, Q, r, R|Y(k)] = \frac{p[Y(k)|X(k), q, Q, r, R] p[X(k), q, Q, r, R]}{p[Y(k)]},
\]

where \( X(k) = [x_0, x_1, \ldots, x_k] \) and \( Y(k) = [y_0, y_1, \ldots, y_k] \). In this equation, the probability of \( [Y(k)] \) is unrelated to the optimization problem, and so it can be rewritten as [37]

\[
J = p[Y(k)|X(k), q, Q, r, R] \times p[q, Q, r, R] \quad (3)
\]

Because the probability of \( [q, Q, r, R] \) represents the probability of process and measurement noise existing, this term can be assumed to be a constant coefficient, because it can be calculated from the a priori information. Hence, the multiplication theorem of conditional probabilities results in

\[
p[X(k)|q, Q, r, R] = \frac{1}{(2\pi)^{y/2} |P_0|^{1/2}} \exp \left\{ -\frac{1}{2} \|x_0 - \hat{x}_0\|_2^2 \right\} \times \prod_{j=1}^{k} \left\{ \frac{1}{(2\pi)^{y/2} |Q|^{1/2}} \exp \left\{ -\frac{1}{2} \|y_j - h(x_j) - r\|_2^2 \right\} \right\}
\]

\[
= \frac{1}{2\pi^n k^{1/2}} |P_0|^{-1/2} |Q|^{-k/2} \exp \left\{ -\frac{1}{2} \|x_0 - \hat{x}_0\|_2^2 \right\} \prod_{j=1}^{k} \left\{ \frac{1}{2\pi^{n/2} |Q|^{1/2}} \exp \left\{ -\frac{1}{2} \|y_j - h(x_j) - r\|_2^2 \right\} \right\}.
\]

(4)

where \( |\Psi| \) and \( |\Psi|^2 = \Psi^T A \Psi \) denote the determinant of the square matrix \( \Psi \) and the quadratic form, respectively, and \( n \) is the process dimension. Now, considering that the measurement sequence is uncorrelated and has dimension \( m \), it can be found that

\[
p[Y_k|X_k, q, Q, r, R] = \prod_{j=1}^{k} p[y_j|x_j, r, R] = \prod_{j=1}^{k} \left\{ \frac{1}{(2\pi)^{m/2} |R|^{1/2}} \exp \left\{ -\frac{1}{2} \|y_j - h(x_j) - r\|_2^2 \right\} \right\} \times \exp \left\{ -\frac{k}{2} \sum_{j=1}^{k} \|y_j - h(x_j) - r\|_2^2 \right\}.
\]

(5)

Substituting Eqs. (4) and (5) into the optimization function of Eq. (3), the estimation problem can be restated as

\[
J = \frac{1}{2\pi^{n(k+1)/2}} \frac{1}{2\pi^{n k/2}} \frac{1}{|P_0|^{-1/2} |Q|^{-k/2} |R|^{-k/2}} \prod_{j=1}^{k} p[q, Q, r, R] \times \exp \left\{ -\frac{1}{2} \|x_0 - \hat{x}_0\|_2^2 \right\} \times \exp \left\{ -\frac{1}{2} \sum_{j=1}^{k} \|y_j - h(x_j) - r\|_2^2 \right\} \times \prod_{j=1}^{k} \left\{ \frac{1}{2\pi^{n/2} |Q|^{1/2}} \exp \left\{ -\frac{1}{2} \|y_j - h(x_j) - r\|_2^2 \right\} \right\}
\]

\[
= C |Q|^{-k/2} |R|^{-k/2} \times \exp \left\{ -\frac{1}{2} \sum_{j=1}^{k} \|y_j - h(x_j) - r\|_2^2 \right\} \times \prod_{j=1}^{k} \left\{ \frac{1}{2\pi^{n/2} |Q|^{1/2}} \exp \left\{ -\frac{1}{2} \|y_j - h(x_j) - r\|_2^2 \right\} \right\},
\]

(6)

where

\[
C = \frac{1}{2\pi^{n(k+1)/2}} \frac{1}{2\pi^{n k/2}} \frac{1}{|P_0|^{-1/2} |Q|}.
\]
\( \times \exp \left\{ -\frac{1}{2} \| x_0 - \hat{x}_0 \|^2 \right\} \) (7)

is a constant coefficient.

Now, the optimization problem can be solved by calculating the derivative of \( J \) with respect to the noise statistics, as follows:

\[
\hat{q}_k = \frac{1}{k} \sum_{j=1}^{k} \left\{ \left[ \hat{x}_j - f_{j-1}(\hat{x}_{j-1}, u_{j-1}) - q \right] \\
\times \left[ \hat{x}_j - f_{j-1}(\hat{x}_{j-1}, u_{j-1}) - q \right]^T \right\}
\]

\[
\hat{y}_k = \frac{1}{k} \sum_{j=1}^{k} \left\{ \left[ y_j - h_j(\hat{x}_{j|i-1}) - r \right] \\
\times \left[ y_j - h_j(\hat{x}_{j|i-1}) - r \right]^T \right\}
\]

\[
\hat{r}_k = \frac{1}{k} \sum_{j=1}^{k} \left[ y_j - h_j(\hat{x}_{j|i-1}) \right]
\]

In Eq. (8), \( f_{j-1}(\hat{x}_{j-1}, u_{j-1}) = f(\hat{x}_{j-1}, u_{k-1}) \) and \( h_j(\hat{x}_{j|i}) = h(\hat{x}_{k}) \). Assuming that the calculated posteriori mean and covariance for \( \varepsilon_k = \hat{y}_k - \hat{x}_k \) are sufficiently accurate, it can be concluded that \( E[\varepsilon_k] \approx 0 \). Hence, considering the \( \hat{x}_k^+ = f_{k-1}(\hat{x}_{k-1}, u_{k-1}) + q, \hat{y}_k = h_k(\hat{x}_k^+) + r \), and \( \hat{x}_k - \hat{x}_k^+ = K_k \varepsilon_k \) equations from the EKF algorithm, the means of \( \hat{q}_k \) and \( \hat{r}_k \) can be calculated as follows:

\[
E[\hat{q}_k] = \frac{1}{k} \sum_{j=1}^{k} E\left[ \hat{x}_j - f_{j-1}(\hat{x}_{j-1}, u_{j-1}) \right]
\]

\[
= \frac{1}{k} \sum_{j=1}^{k} E\left[ \hat{x}_j - \hat{x}_j^+ + q \right] = \frac{1}{k} \sum_{j=1}^{k} E\left[ K_j \varepsilon_j + q \right] = q
\]

\[
E[\hat{r}_k] = \frac{1}{k} \sum_{j=1}^{k} E\left[ y_j - h_j(\hat{x}_j) \right]
\]

\[
= \frac{1}{k} \sum_{j=1}^{k} E\left[ y_j - \hat{y}_j + r \right] = \frac{1}{k} \sum_{j=1}^{k} E\left[ \varepsilon_j + r \right] = r
\]

It can be observed that the estimated \( \hat{q}_k \) and \( \hat{r}_k \) means are unbiased. To calculate the noise covariances \( \hat{Q}_k \) and \( \hat{R}_k \), it can be observed that

\[
\hat{R}_k = \frac{1}{k} \sum_{j=1}^{k} \left[ \left[ y_j - \hat{y}_j \right] \left[ y_j - \hat{y}_j \right]^T \right] = \frac{1}{k} \sum_{j=1}^{k} \left( \varepsilon_j \varepsilon_j^T \right)
\] (10)

Considering the fact that \( E\left[ \varepsilon_k \varepsilon_k^T \right] = P_{yy,k} = H_k P_k^- H_k^T + R \), it is obtained

\[
E\left[ \hat{R}_k \right] = \frac{1}{k} \sum_{j=1}^{k} E\left[ \varepsilon_j \varepsilon_j^T \right]
\]

\[
= \frac{1}{k} \sum_{j=1}^{k} \left( H_j P_j^- H_j^T + R \right) = \frac{1}{k} \sum_{j=1}^{k} \left[ H_j P_j^- H_j^T \right] + R
\] (11)

It is obvious that the estimate for \( \hat{R}_k \) is biased. Therefore, to obtain an unbiased estimation it can be taken

\[
\hat{R}_k = \frac{1}{k} \sum_{j=1}^{k} \left( \varepsilon_j \varepsilon_j^T - H_j P_j^- H_j^T \right)
\] (12)

A similar calculation holds for \( \hat{Q}_k \). Considering the equations

\[
P_k^- = F_{k-1} P_{k-1}^+ F_{k-1}^T + Q
\]

\[
P_k^+ = P_k^- - K_k P_{yy,k} K_k^T
\] (13)

from the EKF algorithm, the unbiased estimation of \( \hat{Q}_k \) can be calculated as

\[
E\left[ \hat{Q}_k \right] = \frac{1}{k} \sum_{j=1}^{k} E\left[ (\hat{x}_j - \hat{x}_j^-) (\hat{x}_j - \hat{x}_j^-)^T \right]
\]

\[
= \frac{1}{k} \sum_{j=1}^{k} K_j E\left[ \varepsilon_j \varepsilon_j^T \right] K_j^T = \frac{1}{k} \sum_{j=1}^{k} \left( P_j^- - P_j^+ \right)
\]

\[
= \frac{1}{k} \sum_{j=1}^{k} \left[ F_{j-1} P_{j-1}^+ F_{j-1}^T + Q - P_j^+ \right]
\]

\[
\Rightarrow \hat{Q}_k = \frac{1}{k} \sum_{j=1}^{k} \left[ K_j \varepsilon_j \varepsilon_j^T K_j^T + P_j^+ - F_{j-1} P_{j-1}^+ F_{j-1}^T \right]
\] (14)

Now, rewriting the estimated means and covariances as recursive formulas, the summarized algorithm of adaptive EKF is given in Algorithm 2.

The performance of the adaptive EKF algorithm given in Algorithm 2 is improved by adding the innovation term \( \xi_k \) and forgetting-factor term \( \Gamma_k \). In some cases, it is possible that the subtractions in the \( \hat{Q}_k \) and \( \hat{R}_k \) formulas result in negative values. To prevent such cases, the following modified formulas can be utilized instead:

\[
\hat{R}_k = \hat{R}_{k-1} + \Gamma_k H_k P_k^- H_k^T
\]

\[
\hat{Q}_k = \hat{Q}_{k-1} + \Gamma_k F_{k-1} P_{k-1}^- F_{k-1}^T
\] (15)

2) ACTUATOR FAULT MODEL

Assume that the actuator faults are modelled in the nonlinear dynamical system as

\[
\dot{x}_1 = x_2
\]

\[
\dot{x}_2 = f(x) + b(x)(1 - \rho) u + d(t)
\]

\[
\rho = \text{diag} \{ \rho_1, \rho_2, \ldots, \rho_k \}
\] (16)
where the states of the system are represented by $x \in \mathbb{R}^n$. Furthermore, the dynamic system is represented by nonlinear functions $f(x)$ and $b(x) \neq 0$, in which $\|d(t)\| \leq d_m$ denotes an external disturbance where $d_m > 0$ is a constant, and $\rho$ is a positive value between zero and one ($\rho \in [0, 1]$). Here, $\rho_j = 0$ represents a fault-free condition, while $\rho_j = 1$ represents a complete failure in the $j$th actuator. Any other value represents a partial effectiveness loss for the actuator.

The FDD module is utilized to identify the effectiveness loss of each actuator. In other words, the A-AEKF algorithm is employed to estimate the value of the $\rho$ parameter for each actuator. The augmented filtering technique is used to achieve simultaneous estimation of the states and parameters. Assuming that the fault parameters exhibit small changes over time, the dynamical model of these parameters can be formulated as

$$\rho_k = \rho_{k-1} + r_{k-1}$$  \hspace{1cm} (17)

where $r_k$ is a zero-mean Gaussian noise. The small changes in the parameters are modelled as additive noise with a small covariance. Augmenting Eq. (17) with the system’s state in Eq. (1) results in

$$\begin{bmatrix} x_k \\ \rho_k \end{bmatrix} = \begin{bmatrix} f(x_{k-1}, u_{k-1}) + w_{k-1} \\ \rho_{k-1} \end{bmatrix}$$ \hspace{1cm} (18)

which can be represented using $X_k$ as

$$X_k = \Psi(\Omega_{k-1}) + \begin{bmatrix} w_{k-1} \\ r_{k-1} \end{bmatrix}$$ \hspace{1cm} (19)

Now, the purpose of the proposed A-AEKF algorithm is to estimate the matrix $X_k$, which contains the augmented values of the fault parameters and the system’s states.

3) DECISION MAKING

The decision-making process is conducted using a fixed threshold [38]. Consider the vector of residuals $r_{\rho_i}(t)$. Threshold-old tests are applied to each residual as

$$g_{\rho_i}(t) = \begin{cases} 1, & |r_{\rho_i}(t)| \geq T_{h,i} \\ 0, & |r_{\rho_i}(t)| < T_{h,i} \end{cases}$$ \hspace{1cm} (20)

The value of $g_{\rho_i}(t)$ indicates whether the residuals exceeded the threshold $T_{h,i}$. This threshold is calculated through trial and error. Different fault-free scenarios are simulated to acquire and monitor residual signals. Furthermore, cases with different noise statistics and external disturbances are simulated, and in each case the maximum value of the residual is extracted. Evaluating these values, a fixed threshold of $T_{h,i}$ is obtained. In other words, in a fault-free situation the generated residuals will be below this threshold. Because any noise statistics and external disturbances can be considered in selecting these thresholds, the violation of such a threshold indicates a faulty condition.

B. NON-SINGULAR TERMINAL SYNERGETIC CONTROL

Consider the fault-free ($\rho_j = 0$) second-order nonlinear system in Eq. (16). A non-singular terminal surface can be defined as

$$s(x) = e + \left(1 - \frac{1}{\beta}\right)\text{sgn}(e)|\dot{\dot{e}}|^{p/q}$$  \hspace{1cm} (21)

where $e = x_1 - x_d$ and $\dot{e} = \dot{x}_1 - \dot{x}_d$. Furthermore, $\beta$ is a positive constant, and $p$ and $q$ are odd positive integers that should satisfy $1 < p/q < 2$. Assume that the synergetic macro-variable is defined as a function of the system’s states:

$$\psi = s(x)$$ \hspace{1cm} (22)

The synergetic manifold, which will drive the system states to the defined macro-variable manifold, can be expressed as

$$\mu \dot{\psi} + \psi = 0$$ \hspace{1cm} (23)
where the parameter $\mu$ is a positive integer value that affects the value of the control signal and convergence speed [39]. Substituting the non-singular terminal surface given in Eq. (21) into the defined macro manifold of Eq. (22) gives the following non-singular terminal synergetic (NTS) manifold:
\[
\mu \left( \dot{\varepsilon} + \frac{p}{q\beta} |\dot{\varepsilon}|^{q-1} \right) + e + \left( \frac{1}{\beta} \right) \text{sgn}(e) |\dot{\varepsilon}|^{p/q} = 0 \tag{24}
\]

Considering the defined error and its derivative from Eq. (21), as well as the fact that $\ddot{\varepsilon} = \ddot{x} - \ddot{x}_d$, the control law for the second-order nonlinear system can be obtained from Eq. (24) as
\[
u = -b^{-1}(x) \left\{ f(x) + d_m - \ddot{x}_d \right\} + \frac{q\beta}{p\mu} |\dot{\varepsilon}|^{q/p} \left( \mu \dot{\varepsilon} + e + \left( \frac{1}{\beta} \right) \text{sgn}(e) |\dot{\varepsilon}|^{p/q} \right) \tag{25}
\]

To prove the stability of the proposed controller, the positive definite Lyapunov candidate function $V = 0.5\psi^T \psi$ is considered, the derivative of which is $\dot{V} = \psi^T \dot{\psi}$. It can be concluded from Eq. (23) that $\dot{\psi} = -\frac{1}{\mu} \psi$. Therefore,
\[
\dot{\psi} = -\frac{1}{\mu} \psi^T \psi = -\frac{1}{\mu} ||\psi||^2 \leq 0, \tag{26}
\]
which completes the proof.

The proposed controller can be developed using the faulty system defined in Eq. (16). From Eq. (16) it can be concluded that $\ddot{x} = f(x) + b(x)(1 - \rho)u + d(t)$. Therefore, considering the defined tracking error as $e = x - \dot{x}_d$, the second derivative of $e$ would be:
\[
\ddot{e} = \ddot{x} - \ddot{x}_d = f(x) + b(x)(1 - \rho)u + d(t) - \ddot{x}_d \tag{27}
\]

Considering the NTS manifold in Eq. (24) and the tracking error in Eq. (27), it can be concluded that
\[
\mu \left( \dot{\varepsilon} + \frac{p}{q\beta} |\dot{\varepsilon}|^{q-1} \right) + e + \left( \frac{1}{\beta} \right) \text{sgn}(e) |\dot{\varepsilon}|^{p/q} = 0
\]
\[
\mu \left( \dot{\varepsilon} + \frac{p}{q\beta} |\dot{\varepsilon}|^{q-1} \right) + e + \left( \frac{1}{\beta} \right) \text{sgn}(e) |\dot{\varepsilon}|^{p/q} = 0
\]

The control law based on the proposed non-singular terminal synergetic FTC (NTSC-FTC) can be represented as
\[
u = -(b(x)(1 - \rho))^{-1} \left\{ f(x) + d_m - \ddot{x}_d + \frac{q\beta}{p} |\dot{\varepsilon}|^{1-q/p} \right\} + \frac{q\beta}{p\mu} |\dot{\varepsilon}|^{1-q/p} \left( e + \left( \frac{1}{\beta} \right) \text{sgn}(e) |\dot{\varepsilon}|^{p/q} \right) \tag{29}
\]

In this equation, the actuator fault parameter $\rho$ will be detected using the proposed A-AEKF.

**Theorem 1:** Under an actuator fault, the states of Eq.16 with the controller in Eq.29 converge to zero in finite time.

**Proof:** Considering the Lyapunov function $V = 0.5\psi^T \psi$, the Lyapunov stability can be proven using Eq. (26).

**C. INTERVAL TYPE-2 FUZZY SATIN BOWERBIRD OPTIMIZATION (IT2FSBO)**

This subsection introduces a newly developed optimization algorithm. The idea behind this algorithm is motivated by the behaviour of the satin bowerbird in nature [40]. The interesting aspect of its behaviour concerns the building of bowers to attract a female. The female chooses a mate based on various parameters including its bower, with different decorations such as flowers, and its vocalizations. Regarding this behaviour, the algorithm is introduced in the following steps:

1) Generating bowerbirds: The First generation of possible solutions are generated as random numbers for $i = 1, \ldots, N$
\[
SB_i = B_{min} + \text{rand} \ast (B_{max} - B_{min}) \tag{30}
\]

where $SB_i$ represents the $i$th bird among the whole population of size $N$. Upper and lower bounds of the searching space are given as $B_{max}$ and $B_{min}$, respectively. The parameter “rand” is a random number from $[0,1]$.

2) Probability calculation: For each candidate solution, the probability is calculated as
\[
P_i = \frac{f_i'}{\sum_{n=1}^N f_n'}
\]
\[
f_i' = \begin{cases} 1 & f(SB_i) \geq 0 \\ 1 + \frac{1}{f(SB_i)} & f(SB_i) < 0 \end{cases} \tag{31}
\]

where $P_i$ and $f_i$ represent the probability and the fitness value for the $i$th candidate satin bowerbird, respectively. The probability parameter is defined as the criteria to determine the attraction of each candidate for a female bowerbird.

3) Choosing the elite bird: Like other meta-heuristic algorithms, finding the best candidate solution helps to improve the searching procedure. In this step, the candidate solutions are sorted in terms of their fitness values, and the bird with the best value is selected as the
The overall presentation of an interval type-2 fuzzy system is implemented to update the parameter α at each iteration based on information from the previous iteration. To resolve this, in this study an interval type-2 fuzzy system is implemented to update the parameter α in the previous iteration. This parameter is important because it affects the new generation of candidate solutions. The new variable which is called footprint of uncertainty (FOU), considering μ̃(x, θ) = 1, the fuzzy membership function is limited by lower membership function μ̃(x, θ) and upper membership function μ̃(x, θ). This definition creates a new variable which is called footprint of uncertainty (FOU), which helps the system to deal with uncertainty [46], [47]. The overall presentation of an interval type-2 fuzzy system can be summarized as Fig. 2.

Considering the general presentation of interval type-2 fuzzy system, which is given in Fig. 2, different parts of the system can be explained as following:

1) **Fuzzifier:** As type-1 fuzzy systems, it is necessary to have some rules to connect each set of inputs to one of the outputs. These connections are defined in this section and each one named as a rule. These connections can be shown as:

\[ R^i : \text{If } \psi_1 \text{ is } \tilde{\Theta}_1^i \text{ and } \ldots \text{, and } \psi_k \text{ is } \tilde{\Theta}_k^i \text{ Then } y \text{ is } Y^i, \]

where the inputs of the fuzzy system, and the related fuzzy set are given by \( \psi_i, i = 1, \ldots, k, \) and \( \tilde{\Theta}_n^i, \) respectively. On the other hand, the outputs of the fuzzy system and related fuzzy sets are shown by \( y, \) and \( Y^i, \) respectively.

2) **Inference:** The implementation of fuzzy rules to create output of the system based on inputs is done by interface block in an interval type-2 fuzzy system. The rule-firing interval can be formulated as

\[ F^i(\psi) = \left[ f^i_1, f^i_2 \right] \]

where \( f^i_1 = \left[ \bar{\mu}_{\tilde{\Theta}_1^i}(\psi_1) \times \cdots \times \bar{\mu}_{\tilde{\Theta}_k^i}(\psi_k) \right] \)

\[ f^i_2 = \left[ \bar{\mu}_{\tilde{\Theta}_1^i}(\psi_1) \times \cdots \times \bar{\mu}_{\tilde{\Theta}_k^i}(\psi_k) \right] \]

3) **Type reducer:** Type-2 fuzzy system should be changed into a type-1 fuzzy system which is done by type reducer block. This reduction is done in centre-of-sets (cos)-type reduction way and can be formulated as

\[ Y_{\cos}(\psi) = \bigcup_{f^i \in F^i} \frac{\sum_{i=1}^{M} y^i f^i}{\sum_{i=1}^{M} f^i} \]
TABLE 1. The fuzzy rules of the system.

| \( \mu \) | \( \eta_n \) | \( S \) | \( M \) | \( B \) |
|---|---|---|---|---|
| \( \eta_1 \) | \( \eta_2 \) | \( \eta_3 \) | \( \eta_4 \) | \( \eta_5 \) |
| \( y_l \) | \( y_r \) | \( y \) |

\[
y_l = \frac{\sum_{i=1}^{L} \bar{y}^i f_i + \sum_{i=L+1}^{M} \bar{y}^i f_i}{\sum_{i=1}^{L} f_i + \sum_{i=L+1}^{M} f_i}
\]

\[
y_r = \frac{\sum_{i=1}^{R} \bar{y}^i f_i + \sum_{i=R+1}^{M} \bar{y}^i f_i}{\sum_{i=1}^{R} f_i + \sum_{i=R+1}^{M} f_i}
\]

\[
y = \frac{y_l + y_r}{2}
\]

where the number of fuzzy sets and the switching points are given by \( M, L, \) and \( R \), respectively.

- Defuzzifier: Calculation of fuzzy sets output is performed by defuzzifier block as:

\[
y = \frac{y_l + y_r}{2}
\]

The presented IT2FS is utilized to update the \( \alpha \) parameter as follows. The input of the fuzzy system is selected as \( h_1 = f_{\text{elite}} - f_i \) and \( h_2 = f_i - f_{i-1} \). Based on these definitions, the fuzzy rules are illustrated in Table 1. The variables in Table 1 denote \( S = \text{Small}, M = \text{Medium}, \) and \( B = \text{Big} \). The membership functions of the output are set as constants, and can be expressed as follows:

\[
S \equiv \begin{cases} \beta_S = 0.05 \times \gamma \\ \bar{\beta}_S = 0.15 \times \gamma, \end{cases}
M \equiv \begin{cases} \beta_M = 0.45 \times \gamma \\ \bar{\beta}_M = 0.55 \times \gamma, \end{cases}
B \equiv \begin{cases} \beta_B = 0.85 \times \gamma \\ \bar{\beta}_B = 0.95 \times \gamma, \end{cases}
\]

where the \( \gamma \) parameter takes a positive value, which can be tuned by the designer.

2) VALIDATION OF IT2FSBO

It is necessary to perform supplementary tests to validate the reliability of the proposed optimization algorithm, and to compare it with traditional optimization algorithms. This comparison can provide a more comprehensive overview of the performance of the proposed method compared with others. For this purpose, the algorithm is applied to benchmark problem of different types, which can be categorized into two major groups: unimodal and multimodal functions. Information on these functions is provided in Table 2. The proposed method is compared with the genetic algorithm, particle swarm optimization, differential evolution, and a basic satin bowerbird algorithm.

As can be observed in Table 3, the proposed algorithm outperforms the basic algorithm. For almost all the benchmark problems, the proposed IT2FSBO algorithm obtained better results and a lower cost value than the basic approach. In comparison with the well-known traditional evolutionary algorithms, the results show that the proposed algorithm represents a reliable approach for finding the optimum solutions for different problems. To investigate the performance for solving a real-world engineering problem, the proposed approach is applied to optimize the performance of the fault tolerant controller proposed in this study. The results of this application are presented in the following sections.

The flowchart of the NTSC-IT2FSBO tuning algorithm is sketched in Fig.3. As it can be seen, the proposed optimization algorithm is running alongside the proposed NTSC controller to adjust the tuning parameters of the NTSC.
D. OVERALL SCHEME OF THE PROPOSED ACTIVE FTC SYSTEM
The proposed approach can be described as follows:
1) Acquire the dynamic model of the system using Eq. (1).
2) Augment the actuator fault parameters using the main dynamic model in Eq. (19).
3) Run the proposed IT2FSBO optimization algorithm to adjust the tuning parameters of the controller based on the flowchart given in Fig. (3).
4) Simulate different fault-free scenarios to obtain the fixed threshold of Eq. (20) for the decision-making procedure.
5) Implement the adaptive augmented EKF given in Algorithm 2 to estimate the states of the system and faulty parameters.
6) Design a non-singular terminal synergetic controller using Eq. (29).
7) Reconfigure the proposed non-singular terminal synergetic controller to obtain a fault-tolerant structure based on the diagnosed faults through A-AEKF FDD algorithm.

In other words, initially, the system runs in an offline mode for two reasons; (1) to adjust the tuning parameters of the NTSC using the IT2FSBO optimization algorithm, (2) to obtain the fixed threshold for the decision-making procedure. Then, in an online mode, the FDD module and the reconfiguration mechanism are implemented to provide an active fault tolerant control scheme to handle different actuator faults.

TABLE 5. Root-mean-square estimation errors for the robotic manipulator affected by noises with constant statistics.

| Method     | \(\theta_1\)   | \(\theta_2\)   | \(\hat{\theta}_1\) | \(\hat{\theta}_2\) |
|------------|----------------|----------------|---------------------|---------------------|
| Adaptive EKF | 0.0044        | 0.0187        | 0.0213              | 0.0061              |
| EKF         | 0.2583        | 0.0253        | 0.0781              | 0.0160              |

III. SIMULATION AND RESULTS
This section illustrates the performance of the proposed FDD and FTC modules when applied to a 2-DoF robotic manipulator under various fault scenarios. First, the accuracy of the A-AEKF is demonstrated compared to conventional EKF, to address the impact of the noise statistics on the residual signal generation performance. Second, the performance of NTSC is studied compared to the sliding mode controller. The robustness of the synergetic controller is also demonstrated, and the performance of the FTC module is assessed.

A. 2-DOF ROBOTIC MANIPULATOR DYNAMICS
Consider a 2-DoF robot with the dynamic model

\[
D(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + g(\theta) = u
\]

where \(D(\theta) \in R^{2 \times 2}\), \(C(\theta, \dot{\theta})\dot{\theta} \in R^{2}\), \(g(\theta) \in R^{2}\), and \(u\) represent the inertia, the centripetal and Coriolis matrix, the gravitational force, and the exerted joint input. Detailed information on this robot can be found in [49]. The parameter values of the robot are presented in Table 4.
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TABLE 6. Root-mean-square estimation errors for the robotic manipulator affected by noises with time-varying statistics.

| Method      | $\hat{\theta}_1$ | $\hat{\theta}_2$ | $\hat{\delta}_1$ | $\hat{\delta}_2$ |
|-------------|-------------------|-------------------|-------------------|-------------------|
| Adaptive EKF| 0.0003            | 0.0062            | 0.0024            | 0.0081            |
| EKF         | 0.1969            | 0.1316            | 0.4845            | 1.3661            |

Assume that the covariances of the noises are defined as follows:

- for $t < 5$ s, $Q = 10^{-6}I_{2 \times 2}$, $R = 10^{-6}I_{2 \times 2}$;
- for $5 \leq t \leq 15$ s: $Q = 10^{-3}I_{2 \times 2}$, $R = 10^{-3}I_{2 \times 2}$;
- for $t > 15$ s, $Q = 10^{-6}I_{2 \times 2}$, $R = 10^{-6}I_{2 \times 2}$;

Fig. 5 illustrates the performances of the Kalman filters with time-varying noise statistics.

Changes in the noise powers can be observed in Figs. 5b and 5d. It can be observed that before these changes, the EKF algorithm can estimate the true values of the states. However, when the noise covariances change the EKF is unable to converge to the true values and diverges, while the proposed adaptive EKF continues to estimate the values even in this case. The RMSE metric in Table 6 provides further information regarding the adaptive EKF and EKF performances in the case of time-varying noises.

The accuracy of estimating the true values, and hence generating accurate residual signals, plays a critical role in detecting, isolating, and identifying the fault parameters of the actuators. To study the importance in this aspect, the following scenario is considered.

TABLE 7. First scenario: Partial effectiveness loss of actuators at different times.

| Actuator | $\rho_1$ | $\rho_2$ |
|----------|----------|----------|
| Time(s)  | 10       | 15       |
| Partial loss | 0.7  | 0.4      |

Assume that the actuators are affected by the faults given in Table 7, which are present in different time periods. This means that, for instance, the first actuator loses 70% of its effectiveness after $t = 10$ s, and works at only 30% of its strength. As FDD modules, the A-AEKF and AEKF are adopted to detect the faults in Table 7. In this case, it is assumed that the real unknown noise covariances are $\hat{Q} = 10^{-7}I_{2 \times 2}$ and $\hat{R} = 10^{-3}I_{2 \times 2}$, and the assumed covariances are $\hat{Q} = 10^{-20}I_{2 \times 2}$ and $\hat{R} = 10^{-20}I_{2 \times 2}$. The values of the thresholds defined in Eq. (20) are obtained through trial and error, and are set to $T_{h,1} = 0.05$ and $T_{h,2} = 0.06$ for the first and second actuator, respectively. Fig. 6 illustrates the difference between the FDD modules. It can be observed that the AEKF algorithm is not capable of providing an accurate estimate of the fault parameters. The role of the noise covariances in the performance of the Kalman filter can be observed from this figure. On the other hand, the proposed adaptive scheme for predicting the noise covariances at each step is capable of fully monitoring the fault parameters, and provides accurate information regarding the fault size, time, and location.
The detected and diagnosed actuator faults corresponding to the first scenario are illustrated in Table 8.

One important feature of the FDD module is its ability to detect and estimate simultaneous occurrence of actuator faults with different values. Table 9 describes the second scenario. The faults occurred at $t = 7$ sec and the thresholds are 0.03 for both actuators.

Fig. 7 illustrates the performances of the FDD modules based on the A-AEKF and AEKF methods. As expected, the EKF-based algorithm is completely unable to estimate the fault parameters, while A-AEKF yields a better performance than AEKF. The A-AEKF is capable of detecting simultaneous actuator faults with a high accuracy. The detected and diagnosed times and values of the faults are presented in Table 10.

Thus, the accuracy of the proposed A-AEKF approach has been demonstrated as the FDD module in different possible scenarios. Next, the performances of the proposed controller and FTC scheme will be discussed.

C. FTC MODULE PERFORMANCE STUDY

As mentioned in Section I, solutions proposed to overcome the chattering phenomenon for sliding mode-based controllers affect the robustness and performance of the controlled system. In this study, a non-singular terminal synergistic controller is introduced, which not only effectively mitigates chattering, but also preserves the system performance in the presence of external disturbances. Therefore, the performance of the proposed NTSC-IT2FSBO will be illustrated in comparison to the non-singular terminal sliding mode control (NTSMC) introduced in [27]. Subsequently, the overall performance of the FTC scheme combined with the FDD module will be discussed.
The NTSMC has the sliding surface of \( s = e + \frac{1}{\beta_{ntsmc}} \frac{p}{q} \frac{\dot{e}}{\dot{\eta}_{ntsmc}} \). Considering the NTS manifold in Eq. (24). The tuning parameters are assumed to be the same, and equal to \( \beta_{ntsmc} = \beta_{nts} = 10 \) and \( \frac{p}{q}_{ntsmc} = \frac{p}{q}_{nts} = 1.2 \). The tuning parameter \( \mu \) for NTSC-IT2FSBO will be calculated online through the IT2FSBO system. It also assumed that no external disturbances exist, and no chattering alleviation term is adopted in the NTSMC. Considering a desired trajectory for the robot, the performances of NTSC-IT2FSBO and NTSMC are compared in Fig. 8.

From Figs. 8a and 8c, it is obvious that both controllers are capable of tracking the desired trajectory with a high accuracy. However, a close examination of the control signals used to track the trajectories (Figs. 8b and 8d) reveals a more pronounced chattering phenomenon for the NTSMC compared to the proposed synergetic controller. Different methods have been proposed to alleviate the effect of chattering in sliding mode-based controllers. One common method is to replace the discontinuous \( \text{sign} \) function in the switching part of the control with a continuous hyperbolic tangent function [50].

Now, considering the same tuning parameters for the controllers, their performance are studied in the presence of external disturbances of different magnitudes. Consider an external disturbance \( d(x) = \zeta \sin(3t) \) affecting the system after \( t = 5 \) s, where \( \zeta \) represents the size of the disturbance. The performances of the controllers is illustrated in Fig. 9.

Fig. 9 shows that changes in the magnitude of the disturbance have a significant effect on the performance of the sliding mode-based controller, while the proposed NTSC-IT2FSBO exhibits more robust behaviour in the presence of an external disturbance. A close examination of the control signals of both controllers (Fig. 10) for \( \zeta = 10 \) shows that the sliding mode controller yields a chattering-free response. However, as depicted in Fig. 9c, this is achieved at the cost of robustness and performance degradation.

Regarding the effectiveness of the proposed NTSC-IT2FSBO, the necessity of the FTC module will be demonstrated, and the performance of the FTC module based on this controller in various fault scenarios will be discussed. In previous fault scenarios, it was assumed that the noise statistics were unknown but constant in time. Here, they will be assumed to be unknown and time-varying. The performance of the A-AEKF as the FDD module will be illustrated, and the
information gathered by this algorithm will be communicated to the FTC module to reconfigure the controller and maintain system performance.

Consider the third scenario, as shown in Table 11, where partial faults have occurred at different time periods. It is also assumed that the real noise covariances affecting the system are time-varying, and the same as in Section III-B.

The estimated values of the faults are sketched in Fig. 11. The changes in the values of the noise statistics from \( t = 5 \) s to \( t = 15 \) s are obvious. As expected, the AEKF is not able
to converge to the true values of the fault parameters, while the fault detection and diagnosis processes are performed accurately using the A-AEKF with time-varying noise. The extracted values for the time and size of each link’s actuator are presented in Table 12. It should be noted that the fixed threshold for both actuators are 0.03.

Assuming that the external disturbance $d(x) = 5\sin(3t)$ affected the system after $t = 5s$ and providing the FTC module with the information collected on the faults, the performance of the NTSC-IT2FSBO is illustrated in Fig. 12, and also compared with the NTSMC approach. It can be observed from Fig. 12 that the proposed FTC scheme based on the synergetic controller yields a better performance its NTSMC counterpart. Closely examining Fig. 12c at $t = 12s$, when the second link’s fault occurs it can be observed that the

### Table 11. Third scenario: Actuator faults at different times.

| Actuator | $\phi_1$ | $\phi_2$ |
|----------|----------|----------|
| Time (sec) | 10  | 12      |
| Partial loss | 0.8 | 0.5     |

### Table 12. Third scenario: Detected and estimated faults based on the A-AEKF approach.

| A-AEKF FDD module | $\phi_1$ | $\phi_2$ |
|--------------------|----------|----------|
| Time (sec)          | 10.04    | 12.03    |
| Estimated size      | 0.8143   | 0.4980   |
| RMSE                | 0.0072   | 0.0008   |
NTSC-IT2FSBO approach tolerates this fault better than the NTSMC.

IV. CONCLUSION
This paper has proposed an active FTC scheme for a robotic manipulator subject to actuator faults. Actuator faults were detected and identified using an A-AEKF FDD module, capable of simultaneously estimating the faulty actuators and the states of the system in the presence of unknown and/or time-varying noise statistics. The FTC scheme was designed based on a non-singular terminal synergetic control (NTSC), to guarantee finite-time convergence of the states and a chattering-free performance while circumventing the singularity problem of the terminal synergetic control. The proposed controller offers better robustness behaviour than conventional sliding mode controller. A novel satin bowerbird optimization approach utilizing interval type-2 fuzzy logic to optimize its performance was considered to enhance the controller’s performance further. The effectiveness of the approach was assessed using a 2-DoF robotic manipulator subject to different fault scenarios. The obtained results confirmed the fault tolerance capabilities and stable performance of the proposed approach. As for the future work, the experimental evaluation of the proposed methods will be considered by a real robotic system. Another interesting research would be to consider sensor or system faults as well. The capabilities of the proposed methods should be studied and proper modifications might be necessary.

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