Fault Diagnosis and Prognosis for Satellite Formation Flying: A Survey

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ABSTRACT Fault diagnostics and prognosis are vital functions of engineering systems, mainly fault prognosis, which is a relatively novel area and requires further development. By applying these methods, the system can be enriched with the ability to detect and isolate faults before they result in failures; in addition, fault propagation can be predicted, and maintenance can be considered to reduce the risk of severe failure. This paper focuses on the problem of satellite formation fault diagnosis and prognosis in the literature. Multi-satellite networks that cooperate as multi-agent systems are primarily used to implement cutting-edge technologies and improve future Earth and space observing missions. Space systems constantly encounter numerous failures due to the hazards and challenges of the space environment that need to be tackled. The current starts with an overview of the main concepts and motivations behind the deployment of small satellites in constellation settings and the detection and prediction of their faults. Next, recent papers on fault diagnosis and prognosis of single and multiple agent(s) or satellite(s), working individually or in collaboration, are reviewed. Comprehensive comparisons and categorization of the reviewed literature are included throughout the paper leading to existing research gaps for future work.

INDEX TERMS Fault, diagnosis, prognosis, multi-agent systems, satellite formation flying.

I. INTRODUCTION

Multi-Agent System (MAS) refers to the concept that several vehicles work together to meet the objective of a much more complex single vehicle. The most common cooperative control problems involve consensus, formation control, flocking, coverage control, and distributed estimation. By considering the example of satellite formation flying (SFF), we can see multiple small satellites cooperate to reach the goals of one larger, more equipped, and more expensive satellite. Therefore, this area has become one of the most renowned research subjects among many complex systems to be simplified and effective. The MASs are popular in satellite formation control and consensus and well-received in other fields such as multiple robotics distributed control and geological investigation [1]–[3]. One of the main drawbacks of utilizing the MASs strategy is a higher risk of being faulty compared to a single system. Besides that, the fault in one vehicle might spread to its neighbours

through topology connections and finally deteriorate the whole system performance [4], [5]. So, it is crucial to detect and isolate the faulty agent or component before propagation.

Multiple satellites in orbit working together as a MAS are primarily used to implement cross-cutting technologies and improve future Earth and space observing missions. Satellite systems are continuously under threat of various failures, such as structural degradation, sensor faults, actuator faults, connection loss, or component damage, due to the dangers and challenges of the unknown space environment. Therefore, the fault diagnosis for detecting and isolating failures source and fault prognosis for predicting the future behaviour of faulty components can be considered the vital role of space systems' health management process.

Fault diagnosis and, beyond that, Condition-based maintenance (CBM) and prognostics and health management (PHM), which are components of the diagnosis, prognosis, and health monitoring (DPHM) framework, have evolved in recent decades to address the shortcomings of traditional complex system maintenance practices. Consequently, formulating and deploying autonomous systems capable
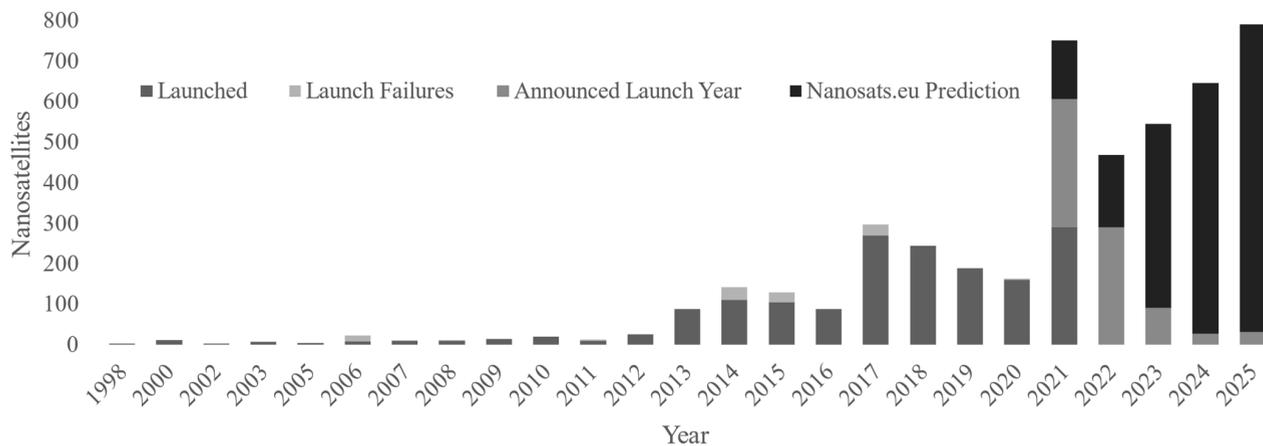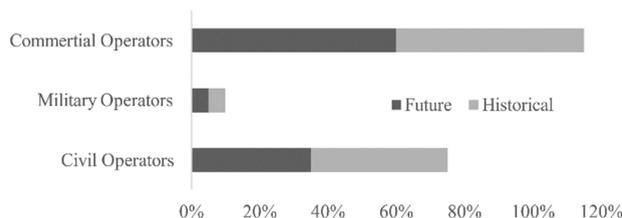
The associate editor coordinating the review of this manuscript and approving it for publication was Francesco Tedesco[iD].

FIGURE 1. Nanosatellite lunches history [11].

FIGURE 2. Satellite operator trends [10].

TABLE 1. Satellite classification by mass [6]–[8].

Class	Mass Range (kg)	Class	Mass Range (kg)
Large	≥1000	Nano	1-10
Medium	500-1000	Pico	0.1-1
Small	<500	Femto	<0.1
Mini	100-500	Atto	<0.01
Micro	10-100	Zepto	<0.001

TABLE 2. Satellites cost of design comparison [8], [9].

Class	Cost (M US $)	Class	Cost (M US $)
Large	>100	Nano	0.5-1
Medium	50-100	Pico	<0.08
Small	<50	Femto	<0.0001
Mini	5-20	Atto	100 US $
Micro	2-3	Zepto	Few $

of self-monitoring and maintenance is critical. This paper provides a comprehensive review of recent studies on DPHM for MASs, followed by DPHM for small satellites in constellation under an undirected/directed communication graph.

The remainder of this paper is structured as follows. The motivation for this literature survey is explained in Section II. In Section III and IV, the model and problem formulation are described in both fault-free and fault-prone scenarios. In Section V, the available literature on the topic is discussed. Finally, the conclusion and suggestions for future work are given in Sections VI and VII, respectively.

II. RESEARCH MOTIVATION

In the modern engineering world, the development and launch of a spacecraft formation mission are complex and require various resources and experts. Scientists and technicians from many disciplines must be employed to perform many research and tests. Systems must be monitored and maintained to prevent any risk of damage and failure in launching a spacecraft, starting from the first stages of design to manufacturing and assembly. Eliminating the risk of mission failure and reducing its probability is essential for researchers and investors.

Satellites can be categorized into three classes in terms of mass: a) large spacecraft, b) medium spacecraft, and c) small spacecraft. When a spacecraft's mass is less than 500 kg, it is classified as a small satellite. TABLE 1 shows each class of satellites with their corresponding mass. As can be observed

in TABLE 1, the small satellites category involves several types of satellites [6]. Because CubeSats are classified as both nanosatellites and microsatellites, the terms are frequently interchanged [7].

The benefits of using smaller satellites in constellations instead of a heavier single satellite encourage researchers to use the cooperation of small satellites to operate tasks of a single heavy agent. First of all, smaller satellites require lower-end launch vehicles and can be launched in multiples. Secondly, they offer the possibility of gathering data at multiple points [9]. Furthermore, the mentioned strategy can improve mission robustness, reduce cost, bring exceptional image resolution, and enhance redundancy. A comparison between the different classes of satellites in terms of cost is provided in TABLE 2. It is proven that the costs of space missions decrease by using smaller satellites.

SpaceWorks Enterprises publishes an annual report on small satellite marketing assessments. Their 2020 report [10] analyses the current developments and provides a potential market for future results until 2025. A total of 189 nano/microsatellites were launched in 2019, a decrease of 25% compared to last year. 2019 was a down-year for
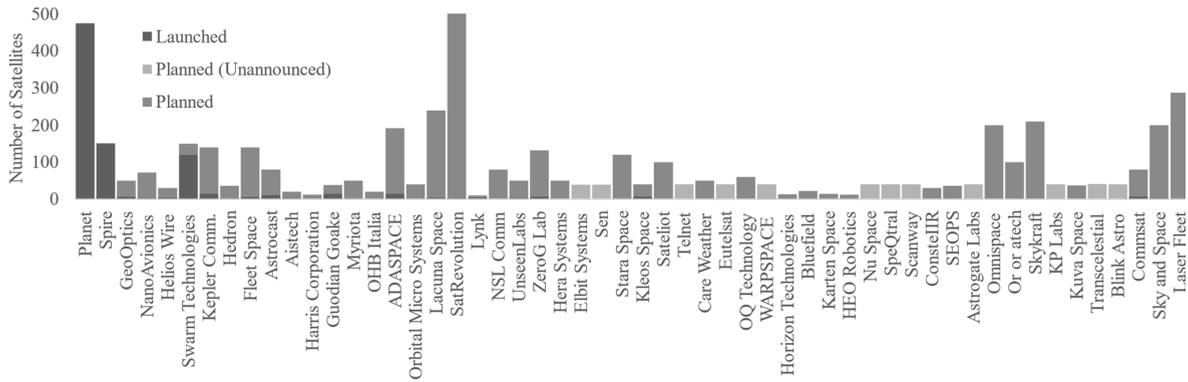
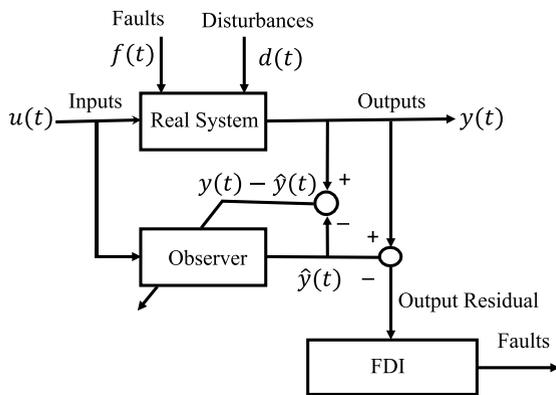**FIGURE 3.** Nanosatellite constellation [11].

FIGURE 4. Observer-based fault detection [19].

the small satellite sector, with only 188 satellites launched vs 294 predicted. The drop in industry performance was primarily due to commercial operators; several significant operators have launched fewer satellites than expected. However, this trend will change in the following years. According to FIGURE 1, the number of nanosatellites' launches is forecasted to grow in the following years. About 2,900 nano/microsatellites will require a launch during 2021-2025. FIGURE 2 presents commercial satellites that will be the majority of the future small satellites deployed in space as the government projects shrink in the upcoming years. FIGURE 3 can be a helpful demonstration in giving insight into satellite constellation. In this research, we are interested in reviewing the provided framework for fault diagnosis and prognosis of small satellites in constellation. FIGURE 3 shows the number of nano/microsatellites launched or planned to be launched in each nanosatellite constellation. The considerable number of nano/microsatellites waiting for launch demonstrates the benefits behind employing a constellation of small satellites rather than one large satellite. As utilizing small satellites in constellation necessitates advanced monitoring systems that can compensate for the lack of hardware redundancy due to smaller design and mass constraints, especially when the spacecraft is not available for maintenance and is on a mission, expanding small satellites in constellation enhance the ability to meet at least partially

the objectives of the mission using other healthy units in the constellation in case any of the units malfunctions or fails.

TABLE 3 presents some examples of small satellite mission failures, emphasizing the importance of proper monitoring systems to avoid such losses. A complete review of small satellite missions that have partially or fully failed while on a mission is available in [12].

A combination of CBM and PHM can help detect, isolate, and predict future failures based on available mathematical system models or historical data to prevent such failures. Therefore, in this study, we are interested in reviewing the possible frameworks for the DPHM of small satellites in the constellation as there seems to be a lack of studies in the literature on the prognosis of monolithic space systems. Additionally, the availability of research work on distributed space systems, including satellites in constellation seems to be lacking in the published work and calls for a review of the existing work that sheds light on the existing challenges and future directions in this field.

III. SATELLITE FORMATION FLYING DESCRIPTION AND PROBLEM FORMULATION-FAULT FREE SCENARIO

Solving the cooperative control problem for a multi-agent system necessitates defining three sections: (i) the information exchange among agents, (ii) knowledge of each agent's dynamics of motion, and (iii) a control law based on the consensus objective [13]. In the following sections, we want to extend the cooperative control method to solve the SFF problem considered for a growing number of space missions. The idea is for spacecraft to work together in cooperative formation to distribute the functionality of more expensive, larger spacecraft. The spacecraft formation consists of N spacecraft and one or more virtual leaders that share partial information with their fellow spacecraft.

A. INTERACTION TOPOLOGY

A directed or undirected communication graph describes the communication between a team of satellites in a formation flight or generally a group of agents in MASs. The communication graph can be static or dynamic. In static

TABLE 3. Summary of small satellite failure [12].

Year	Satellite (Mass)	Cause
2001	BIRD (92 kg)	Failure of 3 of 4 Reaction Wheels
2006	COMPASS (85 kg)	Communication Loss
2010	Hayato (1.5 kg)	No Signal After Deployment
2012	AeroCube-4A (1 kg)	Contact Lost After Wing-Close Command Issued
2014	NanoSatC-Br1(1U)	Battery Failure
2015	OCSD-A (3 kg)	Attitude Control Failure
2016	Pratham (10 kg)	Ground station could not receive satellite downlink to acquire data
2017	Landmapper-BC1 (11 kg)	Communication Loss
2018	D-Star One (3U)	Deployment Failure
2020	Lemur-2 (3U)	Deployment Failure (Reentered)
2021	Kosmos 2551(500 kg)	Not Adjusted In Its Orbit

graphs, the edges remain constant throughout the whole process. On the other hand, the edges of dynamic graphs are time-varying. By considering the graph theory, $g = (v, \varepsilon)$ shows a graph, where $v = \{v_1, v_2, \ldots, v_N\}$ is the nonempty finite set of nodes and $\varepsilon \subseteq v \times v$ is the set of edges. Every edge in a weighted graph is associated with a weight. The elements of adjacency matrix $A = [a_{ij}] \in R^{N \times N}$ indicate the weight of every edge. If a parent node j transmits information to a child node i, we have $(j, i) \in v \times v$ described by $a_{ij} = 1$, otherwise $a_{ij} = 0$. While, directed graph made up of a set of nodes connected by directed edges, in the adjacency matrix of an undirected graph $a_{ij} = a_{ji}$. The degree matrix D is defined as $D = diag\{d_1, d_2, \ldots, d_N\}$, where $d_i = \sum_{j \in N_i} a_{ij}$ to form Laplacian matrix of the graph as $L = D - A$ [14].

B. SYSTEM MODEL
For a group of N spacecraft, the individual spacecraft is modelled as a rigid body with the following dynamic equation for the ith ($i = 1, \ldots, N$) spacecraft [15].

$$J_i \dot{\omega}_i = -\omega_i \times J_i \omega_i + \tau_i \tag{1}$$

where $J_i \in R^{3 \times 3}$ is the mass moment-of-inertia matrix, $\tau_i \in R^3$ is the torque control, $\omega_i \in R^3$ is the angular velocity of the ith spacecraft in a body-fixed frame, and $x^\times \in R^{3 \times 3}$ shows the skew-symmetric matrix given by

$$x^\times = \begin{bmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{bmatrix} \tag{2}$$

The kinematic equation of the ith spacecraft in formation is given by [15].

$$\dot{q}_i = T_i(q_i)\omega_i \tag{3}$$

where $\omega_i \in R^3$ is the angular velocity of the spacecraft in a body-fixed frame, $q_i \in R^3$ represents the Modified Rodriguez Parameters (MRPs), which describe the spacecraft attitude with respect to an inertia frame [16].

$$q_i(t) = \rho_i(t)tan\left(\frac{\varphi_i(t)}{4}\right) \tag{4}$$

where ρ_i and φ_i denote the Euler eigenaxis and eigenangle, respectively. The matrix $T_i(q_i) \in R^{3 \times 3}$ for MRPs is given by [15]

$$T_i(q_i) = \frac{1}{2}\left[\frac{1 - q_i^T q_i}{2}I_3 + q_i^\times + q_i q_i^T\right] \tag{5}$$

The spacecraft models in (1) and (3) can be written as follows

$$\dot{q}_i = v_i \tag{6}$$
$$\dot{v}_i = f_i(q_i, v_i) + g_i(q_i)\tau_i \dot{q}_i = v_i \tag{7}$$

For $i = 1, \ldots, N$, where the function $f_i(q_i, v_i) = -T_i\dot{P}_i\dot{q}_i - T_iJ_i^{-1}(P_i\dot{q}_i)^\times J_iP_i\dot{q}_i$, $P_i = T_i^{-1}(q_i)$ and $g_i = T_iJ_i^{-1}$.

C. CONTROL LAW
In the scientific literature, the term SFF describes several different formation estimation architectures (FEA) that allow the production and maintenance of formation state between satellites. These include centralized, distributed, and decentralized architectures [17]:

1) *Centralized estimation architecture* includes a single formation-wide master filter that gathers sensor measurements, control inputs, and spacecraft configuration to estimate the formation states and transmit control signals to all the other spacecraft in the formation. All estimations are carried out at a standard processing station, meaning resource allocation is easy since the master filter fully understands the operations of each spacecraft and has a complete picture of the whole formation. Centralized estimation architecture has some disadvantages: (i) Since state information cannot be obtained from other spacecraft, erroneous readings from one spacecraft will mean the formation will be adversely affected, (ii) The immense computational load imposed on the master filter by global estimation and control, rather than local estimation and control for each spacecraft node, and (iii) There is a high communication overhead because all spacecraft in the formation must be provided with state information by the master filter.

2) *Distributed estimation architecture* uses a hierarchy of filters where each spacecraft runs a local filter, which then provides estimates to the master filter, which is then combined into an estimated formation state. By distributing the spacecraft in formation between various local filters, distributed estimation reduces the computational load of centralized estimation. In this architecture, computation load is distributed among local spacecraft, but it retains the downsides of centralized architecture. Because access to relative states or output between neighbouring satellites is

easier in deep space than absolute information, this design architecture is more acceptable for formation control.

3) *Decentralized estimation architecture* is nonhierarchical, so there is no need for supervision. A decentralized network allows each spacecraft to simultaneously process its measurement data with other spacecraft in formation. However, the total computational burden over the entire formation is more significant than it would be for a monolithic spacecraft. A local data vector must be maintained to minimize data transfer requirements between spacecraft.

The distributed architecture that allows each satellite to communicate with its neighbour makes interagent communication more feasible due to constraints associated with space missions, such as large numbers of small satellites, the location of actuators, the limitation of sensors, and limited wireless ranges. This method is based on local communication between neighbours. Therefore, compared with two other methods is a promising solution for SFF. The rest of this section is dedicated to system general description and formulation for a distributed architecture.

A team of satellites can consist of N followers and M leaders. In most cases, only one leader is involved in distributed tracking problem. The linear or linearized state-space model of the ith followers are demonstrated by

$$\dot{x}_i = Ax_i + Bu_i \tag{8}$$

$$y_i = Cx_i(t) + Du_i(t) \tag{9}$$

where x_i, u_i, and y_i are the state, the input, and the output of satellite in the formation, respectively. A, B, C, D are constant matrices with compatible dimensions. To get a distributed formation, the control law is described by [13]

$$u_i = cK \sum_{j=1}^{N} a_{ij}(x_i - x_j - h_i + h_j) \tag{10}$$

where K is the feedback gain, $c > 0$ is coupling gain, a_{ij} is a corresponding component of the adjacency matrix of satellites' communication graph, and h_i is the formation variable of ith satellite, which satisfied $Ah_i = 0$ criterion. By considering the following two assumptions, we can obtain control feedback gain K and coupling gain c:

Assumption One: (A, B) is stabilizable.

Assumption Two: The satellites' communication graph involves a directed spanning tree.

Note: Each satellite in a directed tree, a directed graph, is connected by a directed edge to the root or leader. Once the root covers all satellites or has directed edges over all nodes, the directed tree is named the directed spanning tree.

1) *Feedback gain* $K = -B^T P^{-1}$, $P > 0$ is determined by solving Linear Matrix Inequality (LMI) below:

$$AP + PA^T - 2BB^T < 0 \tag{11}$$

2) *Coupling gain* $c \geq c_{th}$

$$c_{th} = \frac{1}{minRE(\lambda_i)}, \quad i = 2, \dots, N \tag{12}$$

where $\lambda_i \neq 0$ are eigenvalues of L

To reach formation state, all $A + c\lambda_i BK$ matrices for $i = 2, \dots, N$ must meet Hurwitz stability conditions [18].

As the information on the state of formation is difficult to obtain in many working environments, the relative output information is used to solve the formation control problem. In this case, an observer is designed to estimate the local state information by using the relative output information of a satellite and its neighbours.

$$\dot{v}_i = (A + BF)v_i + cK \sum_{j=1}^{N} a_{ij}[C(v_i - v_j) - (y_i - y_j - C(h_i - h_j))] \tag{13}$$

$$u_i = Fv_i \tag{14}$$

where variables, assumptions, and criteria are described for equation (10), In addition, the term $C(v_i - v_j)$ describes the interaction between satellites and their neighbours when they send virtual outputs of their controllers and F Feedback gain. Observer feedback gains and coupling gain are calculated as follows:

Assumption Three: A, B, C is stabilizable and detectable.

1) *Feedback gain* F must satisfy Hurwitz's stability of $A + BF$.

2) *Feedback gain* $K = -P^{-1}C^T$, $P > 0$ is determined by solving LMI below:

$$AP + PA^T - 2CC^T < 0 \tag{15}$$

3) *Coupling gain* is determined by (12)

Following the above discussion about how cooperative control is used to solve SFF under fault-free conditions. To proceed, we need to understand the effects of fault on SFF, as well as methods for detecting the fault and preventing its propagation.

IV. SATELLITE FORMATION FLYING DESCRIPTION AND PROBLEM FORMULATION-FAULT PRONE SCENARIO

Once a fault has been detected in a system, the control parameters could be modified or the controlling law altered to adapt the system to new working conditions and prevent fault propagation and system failure.

A. FAULT CLASSIFICATION

A system fault mainly occurs in three components: sensors, actuators, and inside the system. Sensor fault may lead to sensor malfunction by producing inaccurate information. A faulty actuator will no longer achieve the desired behaviour of the system. Depending on the fault type, the system may malfunction parametrically or structurally. When a parametric or structural defect is identified, the system model used in fault diagnosis can be modified. In this way, successive faults can be detected using a model of a healthy system.

The classification of dynamic systems' faults based on their form follows: *Abrupt faults* that are sudden and permanent tend to change parameter values much more quickly than normal faults. When a *transient fault* occurs, system variables change transiently. In the case of repeated occurrences, they are classified as *intermittent faults.*

Minor and gradually developing faults are called *Incipient Faults*. The incipient fault is difficult to detect compared to abrupt faults because the uncertainties of the model may mask its effects. It is worth mentioning that *additive faults* and *multiplicative faults* refer to faults that are either added or multiplied to the input of system dynamics. Sensor and actuator fault are added as an external input into the state-space model of the system, so they are called *additive Faults* [19]. An additive fault model of a linear system can be described in state space as

$$\dot{x}_i = Ax(t) + Bu(t) + Kf_a(t) \quad (16)$$

$$y = Cx(t) + Du(t) + Gf_s(t) \quad (17)$$

where A, B, C, D, K, G are constant matrices with compatible dimensions. x, u, y, f_a, and f_s are the state, the input, the output of satellite, actuator fault, and sensor fault, respectively. On the other hand, structural or parametric faults are multiplicative faults that change the state-space model by multiplying a scalar.

$$\dot{x}_i = A(\Theta)x(t) + B(\Theta)u(t) \quad (18)$$

$$y = C(\Theta)x(t) + D(\Theta)u(t) \quad (19)$$

where A, B, C, D are constant matrices with compatible dimensions. x, u, and y are the state, the input, the output of satellite, respectively.

B. SYSTEM MODEL

An observer-based fault detection scheme is employed when an unknown fault ($f(t)$) has occurred in a system and is added along with control input ($u(t)$) and disturbances ($d(t)$) to the real system model. The constant comparison of outputs generated by the sensors ($y(t)$) with outputs derived by the state estimation filter algorithms ($\hat{y}(t)$) can develop an output residual that indicates the presence of the fault by comparing the residual with a threshold. Bayesian filters such as Kalman Filter (KF) or Particle Filter (PF) detect faults when measurement and process are noisy. The detected fault can be isolated by using a bank of filters. If measurement noise is filtered, observers can detect and isolate faults (FIGURE 4).

Fault Detection and Isolation (FDI) architectures, shown in FIGURE 4 for small satellites in a constellation, consist of three major types: decentralized, semi-decentralized (distributed), and centralized [20]. As discussed earlier, distributed architecture compared with two other methods is a more feasible solution for SFF. Therefore, the system general description and formulation for the distributed FDI architecture are discussed below.

Each spacecraft operates its fault detection and fault isolation module using relative interaction between itself and its neighbours in the distributed FDI architecture. System general description and formulation for a distributed FDI architecture is as follow [20],

$$\dot{x}_i(t) = f(x_i) + Bu_i(t) + \omega_i(t) \quad (20)$$

$$y_i = Cx_i(t) + v_i(t) \quad (21)$$

where ω_i and v_i are Gaussian white noise with zero mean and covariance Q and R, respectively. To solve the fault detection problem, first of all, the state of *ith* satellite needs to be estimated utilizing a nonlinear state estimation filter such as extended Kalman filter (EKF), the state of the satellites are estimated and updated in each iteration,

$$\dot{x}_i(t) = f(x_i) + Bu_i(t) + K(t)(y_i(t) - C\hat{x}_i(t)) \quad (22)$$

The Kalman filter gain $K(t) = P(t)(F(t))^T R^{-1}(t)$ is determined by solving the differential Riccati equation:

$$\dot{P}(t) = F(t)P(t) + P(t)(F(t))^T$$
$$-P(t)(C(t))^T (R(t))^{-1} C(t)P(t)$$
$$+Q(t) \quad (23)$$

where Jacobian matrix $F(t) = \frac{\partial f}{\partial x}$ and covariance matrix $P(t_0) = E[(x(t_0) - E[x(t_0)])(x(t_0) - E[x(t_0)])^T]$. The residual signal can be estimated at this stage as the discrepancy between the actual and estimated outputs.

$$e(t) = y(t) - C\hat{x}(t) \quad (24)$$

$e_{ij}(t)$ represents the residual of *jth* actuator of *ith* satellite. Residual dimensions could differ depending on the type of sensor(s) satellites are equipped with. The presence of a fault in satellite formation must be evaluated by defining a threshold. These faults can exist at system, actuator and sensor levels. Additionally, the fault types include abrupt, transient, intermittent and incipient. Consider a matrix $J^i(t)$ is constructed from differences between the residual of *ith* satellite and its closest neighbouring satellite. The residual signal $S^i(t)$ is formed by the summation of rows of $J^i(t)$ and finally, the residual evaluation function is formed as

$$S^i(t) = \sum_{k=1}^{N-1} J_k^i(t) \quad (25)$$

$$d_j^i(m) = \frac{1}{M} \sum_{n=m-M+1}^{m} S_j^i(n) \quad (26)$$

where m and M show sample size and window length, respectively. To select a threshold, the designer(s) must find a criterion that displays the normal and healthy satellite behaviour when faced with the most severe fault.

$$T_j^i = mean(S_j^i(t)) + \sqrt{var(S_j^i(t))} \quad (27)$$

when one of the elements of the residual evaluation function exceeds the threshold T_j^i, a fault is identified. To isolate the detected fault of the system, a threshold is constructed as it was for fault detection,

$$T_{kj}^i = mean(g_{kj}^i(t)) + \sqrt{var(g_{kj}^i(t))} \quad (28)$$

where $g_{kj}^i(m) = \frac{1}{M} \sum_{n=m-M+1}^{m} L_{kj}^i(n)$, $L_{kj}^i(t) = |e_{ij}(t) - e_{kj}(t)|$. L_{lkj}^i shows the effect of detected fault on the *jth* actuator of *kth* satellite of *ith* distributed formation. m and M also show sample size and window length. The mission remains healthy if $g_{kj}^i(m)$ does not exceed its threshold.

After defining the concepts and the problem formulation in previous sections, the available research on fault diagnosis and prognosis in single-agent and multi-agent systems such as SFF is reviewed and compared in the next section.

V. LITERATURE REVIEW

Based on a review of current literature, there are several key themes to consider concerning fault diagnosis of SFF. First, it is essential to review SFF attitude estimation and control methods within this context. Next, a review of the available literature on fault detection, isolation, and prognosis techniques for different purposes is presented. Lastly, fault DPHM for MASs is detailed. Although there is extensive literature on fault diagnosis and prognosis for single systems, cooperative fault diagnosis and prognosis for multi-agent systems, particularly for the formation flying of spacecraft, are still a challenge.

A. SATELLITE FORMATION FLYING STATE ESTIMATION AND CONTROL

In recent years, the problem of attitude coordination control for SFF has received significant attention. SFF is suitable for various space missions, such as Earth and atmosphere monitoring, deep space exploration, and spacecraft servicing and maintenance in orbit.

Maintaining the state of formation between spacecraft, especially in the case of failure of subsystems of satellites, becomes a severe challenge because faults and external disturbances cause a drift in both the position and formation centre of the spacecraft. Modern guidance and navigation systems rely on some form of nonlinear filtering algorithm based on probabilistic inference to compute the state estimate of the spacecraft.

The nonlinear filter estimates the system dynamics by filtering out noisy measurements based on a two-step procedure, iterative process of prediction and correction. Several estimation algorithms have been proposed to estimate the state of SFF; these include KF, EKF, unscented Kalman filter (UKF), and PF.

Carpenter [21] presented the EKF approach to propose a decentralized architecture for autonomous formation establishment and maintenance. Local control was achieved in the reported work by combining local measurement data with transmission vectors from other nodes. Lawton and Beard presented two new control methods for multi-spacecraft attitude alignment to keep the state of formation among satellites during formation manoeuvres [22]. In the case of having more than one leader, Meng *et al.* proposed a distributed attitude containment control that used one-hop and two-hop neighbours' information [23].

Alternately, Kim *et al.* developed an EKF to determine the relative attitude, position, and gyro biases of two spacecraft using line-of-sight (LOS) measurements combined with gyro measurements from each spacecraft. The quaternion was used to describe the attitude kinematics, and general relative orbital equations were used to describe the position in this study [24].

In another study [25], Erdong *et al.* proposed a decentralized variable structure controller using Lyapunov's strategy to handle uncertainty, disturbances, and time delays in satellite interactions. Another application of EKF was introduced by Nebelecky *et al.* [26], where a local EKF and data fusion process known as the Covariance Intersection algorithm were employed to achieve a decentralized attitude estimation between three spacecraft. To control SFF's relative attitude, a state-dependent Riccati equation technique was proposed by Chang *et al.* [27]. Using a lagrangian-based method, Chung *et al.* studied the tracking of multiple satellites cooperatively by a proposed decentralized tracking control law [28].

The EKF was proposed for relative position and attitude estimation for spacecraft formation once more by Xing *et al.* [29]. This study used multiple line-of-sight vector measurements and the EKF to calculate the leader's attitude and relative position. In the subsequent research, Chen *et al.* proposed the integrated Relative Navigation and Attitude Determination (RNAD) approach, which can significantly improve the performance of relative navigation and attitude estimation for ultra-close SFF [30].

Du *et al.* considered a quaternion-based approach for SFF attitude coordination applications. A group of spacecraft under an undirected communication graph cannot be controlled in finite time in the present method. Each spacecraft can use this control strategy to coordinate its attitude with the leader. Additionally, to ease the complicated computation, using a finite-time sliding-mode estimator, it is possible to develop a modified control law to reduce internal satellite communication to communicate with the leader [31].

Zhou *et al.* discussed decentralized finite-time attitude coordination laws using the adaptive sliding mode control technique [32]. It is worth mentioning that each of the formation's spacecraft has its reference trajectory. As a result, when a common time-varying reference attitude is only available to a subset of the group members, the control laws in [32] are not applicable.

Under an undirected communication graph, two distributed velocity-free attitude coordination control methods were developed by Zou [33] to align satellites toward a reference attitude, even when the moment-of-inertia matrices and external disturbances were unknown. Cai and Huang looked at a quaternion-based distributed leader-follower attitude control problem for SFF under an undirected topology graph [34].

To keep the quaternion normalization constraint in estimating the spacecraft attitude and relative position, full state feedback and the Generalized Rodrigues Parameters (GRP) were used in another study by Zhang *et al.* [35]. A sliding mode adaptive control technique was proposed into a Lagrange system to address the problem of distributed attitude control in SFF systems with misaligned actuators by Gao *et al.* [36].

The continuous communication among multiple spacecraft is a common feature of the research mentioned above. In terms of practical applications, such a communication mechanism may consume a significant amount of communication resources. Therefore, using an event-triggered method can improve the process of data transmission. This type of communication is applied on a single satellite in some research, such as in [37]. Despite this, multiple spacecraft achievements remain limited. Spacecraft have internal communication, so it is challenging to design a trigger condition that excludes Zeno behaviour. Using event-triggered inputs, cooperative attitude control of SFFs is pointed in [38]. The interaction between satellites, however, is not yet triggered by events. Motivated by mentioned constraints, Hu *et al.* proposed a cooperative control problem for SFF with resources limitation under an undirected communication graph while considering widespread uncertainty and external disruptions [39]. According to the new framework, neighbour satellites only interact once an event has occurred. So, they need to exchange information only in particular moments. This method significantly reduces their inner satellite interaction load and energy consumption.

A distributed attitude synchronization problem for SFF with constrained and event-triggered communication under a directed topology graph is being proposed by Long *et al.* [40] to save the communication resources. Furthermore, compared to continuous ones, this method has the advantage that it is based entirely on continuous local signals and triggered neighbouring signals. Thus, it requires no constant monitoring of neighbouring states. The papers reviewed in the current section are categorized in TABLE 4.

To lay the foundations for reviewing fault diagnosis, prognosis, and health monitoring for MASs and SFF, the following section reviews the available literature on fault detection, isolation, and prognosis of a single agent.

B. FAULT DIAGNOSIS, PROGNOSIS, AND HEALTH MONITORING

CBM and DPHM have evolved significantly as systems have grown increasingly complex. Furthermore, a high degree of robustness and reliability is also being demanded in various science and technology fields. The following sub-sections will examine the advances in the fields related to this research over the past years.

1) CBM, TBM, AND RUL

The two types of maintenance planning are time-based maintenance (TBM) and CBM. TBM is corrective maintenance that is performed regularly. It is effective but cannot adapt itself to the growing needs for safety. To address this shortcoming, another maintenance method is employed (CBM). Compared to TBM, CBM provides monitoring and controlling of the system to prevent damages and protect the design from the effects of failure [41]. The study [42] compared CBM and TBM, and the difference in performance

between the two methods was noticeable, which is why CBM has gotten more attention in recent years.

The remaining useful lifetime (RUL) prediction can also be used to monitor the system's condition. In terms of practicality and feasibility, RUL prediction is more attractive [43].

2) FAULT DETECTION AND ISOLATION

Fault Diagnosis consists of two parts: the first is attempting to determine fault present in the system, which is called fault detection, and the second is determining the cause of failure, as well as its time and location, which is called fault isolation. FDI has been significantly used as the early part of the DPHM scheme over the last years [44], [45]. The four main types of fault diagnosis [46] are *model-based*, *data-driven, expert, and hybrid* fault diagnosis.

In *model-based* approaches, the mathematical system model is formed in fault-free condition, and then the model estimated states are compared with the measured state. Whenever a significant deviation is detected, it can be an alarm for the presence of the fault. The use of *model-based* fault detection methods was reviewed by Ekanayake *et al.* [47]. The *model-based* approaches can be categorized as stochastic and deterministic methods. State estimate filters working based on the Bayesian framework are considered in stochastic processes. Many applications have used KFs in fault detection [48], and UKFs can also be used in fault detection [49]. Rahimi *et al.* proposed a new hierarchical FDI method for satellite attitude control systems utilizing UKF and adaptive residual window size selection [46]. Adaptive UKF (AUKF) is used for fault estimation and detection of some parts of satellite attitude control system, reaction wheel (RW) and control moment gyros (CMG) to determine the presence of abrupt and intermittent faults by Rahimi *et al.* [50], [51]. The observer or parity relations approach is used in deterministic methods. There is a review of deterministic processes in [52]. In investigating fault diagnosis for spacecraft components, Djebko *et al.* presented a quantitative model-based approach by comparing house-keeping data to data based on a mathematical model of the system [53].

The mathematical model of the system may not always be available due to the system's complexity or lack of deep understanding of it; in these conditions, the *data-driven* approaches are more applicable. Regarding data-driven fault diagnosis methods in space engineering, ElDali and Kumar proposed a data-driven method based on growing neural networks (GNN) and variable sequence Long and Short-Term Memory (LSTM) model to improve the hyperparameter optimization process for fault diagnosis and prognosis of various aerospace applications, including aircraft engines [41]. Furthermore, support vector machines (SVM) are frequently employed in data-driven-based fault diagnosis. Farahani and Rahimi developed an SVM-based FDI algorithm for the satellite CMG [54]. The proposed optimized SVM classifier could detect multiple in-phase faults in a CMG

TABLE 4. Summary of satellite formation flying state estimation and control literature.

Ref.	Architecture	Pros (+) and Cons (−)
[21]	Decentralized	(+) Does not require a central leader
		(+) Minimizing the data transmission
		(+) Improving the robustness of formation operations
		(−) Heavy computational burden over the entire formation
[22]	Distributed	(+) Control strategies are independent of variations in the inertia of spacecraft
		(+) Low-bandwidth communication between neighboring spacecraft
		(+) Formation keeping is guaranteed
		(−) Sever computation loads impose in the master filter
[23]	Distributed	(+) Using finite-time control laws
		(+) Faster convergence, better accuracy, and resilience to errors and disturbances
		(−) Using undirected graph and time-invariant model
[25]	Decentralized	(+) Controlling effects of model uncertainties, external disturbances, and time-varying communication delays
[26]	Decentralized	(+) Overcoming the challenge of unknown correlations
		(+) Better attitude estimation
		(−) High level of complexity
[27]	Decentralized	(+) Guaranteeing the globally asymptotic stability for both the absolute and relative attitude controls
		(+) Improving mission-failure safety of the attitude control algorithm
		(+) Converging the attitude error to zero
		(+) Eliminating unnecessary calculations
[28]	Decentralized	(+) Dealing with complex dynamical networks consisting of highly nonlinear time-varying dynamics
		(+) Reducing Information Network
		(+) Minimizing the tracking and synchronization errors for both rotational and translational motions
[29]	Decentralized	(+) High accuracy for estimating the relative attitude and position of the no-gyro satellite
[31]	Distributed	(+) Using finite-time control laws
		(+) Reducing internal satellite communication to communicate with the leader
		(−) Using undirected graph
[32]	Decentralized	(+) Guaranteeing the tracking errors converge to zero in finite time
		(+) Avoiding singularity problem
[33]	Distributed	(+) Ensuring semiglobal stability
		(+) Guaranteeing the attitude of a rigid spacecraft to track a time-varying reference attitude in finite time
		(−) Using undirected graph
[34]	Distributed	(+) Without assuming that every follower can access the state of the leader
		(+) Generating the desired angular velocity
		(−) Using undirected graph
[36]	Distributed	(+) Dealing with external disturbance and actuator misalignment
		(+) Ensuring the stability and synchronization of the whole closed-loop SFF.
[39]	Distributed	(+) Reducing their inner satellite interaction load and energy consumption
		(+) Dealing with considering mass uncertainties, external disturbances, and limited communication resources
		(+) Avoiding Zeno behavior
		(+) Converging tracking errors to small invariant sets around the origin
		(−) Using undirected graph
[40]	Distributed	(+) Using directed graph
		(+) Requireing no constant monitoring of neighbouring satellites state
		(+) Bounding the close loop signals
		(+) Synchronizing spacecrafts attitude to a common constant vector

assembly. Ibrahim *et al.* proposed a fault diagnosis method to determine failures affecting satellite subparts such as power and communication systems [55]. They classified satellite data using SVMs as faulty or nominal. Next, the data is analyzed logically to determine the patterns of failure. A Fault Tree Analysis has also been performed to correlate the patterns identified with the events leading to the failure [55]. Suo *et al.* designed another SVM-based fault diagnosis strategy by utilizing fuzzy Bayes risk for optimizing the feature selection phase. The defined method enhances the accuracy of classification performance, although it suffers from a long processing time. The presented method is tested on fault diagnoses of the satellite power systems as the satellite power system is subject to 27 percent of all failures [56]. Ganesan *et al.* proposed a fault detector for satellite power system sensors using a convolutional neural network (CNN) to categorize the data. Adding a revised

form of Stockwell transform to this method also significantly improves the data processing procedure [57].

By incorporating unsupervised and supervised machine learning techniques, a new method for fault detection has been developed by Zhang *et al.* [58]. In the first stage, a fault detection method is offered by applying linear discriminant analysis (LDA) to collect historical data as healthy data and satellite in-orbit data as faulty data and then discriminate them from each other by finding the best projection vector. In the next step, a standard model is defined using healthy data and a defined projection vector. Finally, satellite in-orbit faulty data can be detected by recognizing any significant deviation from the normal data of the standard model. The shortcomings of [58] are that LDA is sensitive to nonlinearity, and nongaussian distributions can undermine its efficacy.

DL techniques are also used to propose two new fault diagnosis strategies for satellite attitude control systems.

The first method is designed by Luo *et al.* to link CNN and LSTM to detect actuator bias fault and estimate its magnitude. The results show that merging these two methods can lower estimation error and chattering [59]. The second application of DL is proposed by Xiao and Yin that is related to thruster stuck-open and stuck-close fault diagnosis. The main novelty of the mentioned method is the implementation by using time-domain measurement and the output data of the attitude controller, without access to the mathematical model of the thruster and the satellite attitude control system [60].

However, a lack of historical data can lead to failure in using a data-driven approach. Additionally, this method can cause a heavy computation load. In [61], recent literature on the data-driven and model-based incipient faults diagnosis is reviewed. Furthermore, another study presents a well-covered review on the model-based and data-driven methods by focusing on improving the diagnosability of satellite control systems [62].

A combination of *expert* methods and accurate system knowledge can lead to an accurate fault detection process. Despite its advantages, this method does not have a low cost since it requires expert knowledge and manual checking [63].

In recent years, *hybrid* methods have been developed to improve system reliability and performance; these methods combine various fault diagnosis methods in a different order according to the needs of a problem. In contrast to expert systems, hybrid approaches do not require deep and accurate expert knowledge of the system. Sobhani-Tehrani *et al.* [64] presented a novel hybrid approach to detecting satellite RW faults. They conducted this research using a mathematical model and neural network approaches. A neural parameter estimator (NPE) and two updated NPE structures that comply with updated rules for decision logic and weighting of the FDI under a single-parameter fault model were proposed in this method [64]. In another study [65], Yuan *et al.* employed a hybrid method by using adaptive KF (AKF) and parity equations for FDI of gyroscope and sensor angle. The validity of the proposed approach is proven by numerical simulations of four-axis gyroscopes and star sensors. The study [66] reviewed the fault diagnosis approaches and applications, categorized between knowledge-based and hybrid/active methods.

TABLE 5 summarizes the reviewed papers in this section that deal with the fault diagnosis of the systems. The summary in TABLE 5 includes the methods used in each paper and the applications for each method to help categorize and use-cases for different methods when it comes to fault diagnosis.

3) FAULT PROGNOSIS
Fault prognosis consists of methods to observe the system's condition by monitoring various parameters. After the procedure is observed, a decision would be made on replacing or repairing faulty component(s) depending on the detected fault behaviour. By estimating RUL, it is possible to track the degradation of the systems as a result of the fault to predict the best time for maintenance or employing a redundant

TABLE 5. Summary of fault diagnosis literature.

Ref.	Method	Application
[46]	Model-Based, Stochastic, UKF	Satellite Attitude Control System
[47]	Model-Based	Dynamic Systems
[48]	Model-Based	Engineering Systems
[50], [51]	Model-Based, Stochastic, AUKF	RW and CMG
[52]	Model-Based, Deterministics, Observer	Satellite Attitude Control System
[53]	Model-Based, Quantitive	SONATE Triple Cube Nano-Satellite
[41]	Data-Driven, GNN, LSTM	Aircraft Engine
[54]	Data-Driven, SVM	CMG
[55]	Data-Driven, SVM	Satellite Power and Communication Systems
[56]	Data-Driven, SVM	Satellite Power Systems
[57]	Data-Driven, CNN	Satellite Power Systems
[58]	Data-Driven, LDA	Satellite Attitude Control System
[59]	Data-Driven, CNN and LSTM	Satellite Attitude Control System
[60]	Data-Driven, CNN	Thruster
[61], [62]	Model-Based, Data Driven	Satellite Attitude Control System
[63]	Model-Based, Data-Driven, Expert, and Hybrid	Space Systems
[64]	Hybrid, NPE	RW
[65]	Hybrid, AKF and Parity Equation	Gyroscope and sensor
[66]	Hybrid	Engineering Systems

component or method. This prediction will reduce the cost of maintenance significantly over time. Failure prognosis approaches can be categorized into four groups: *model-based*, *data-driven*, *knowledge-based*, and *hybrid methods*.

A *model-based* fault prognosis approach needs a mathematical model of the system degradation caused by fault(s). The historical or measurement data are used to determine model parameters. So, if a precise failure model is available, it can help predict the system RUL. Estimation and filtering techniques are the main methods for fault prognosis procedure; model-based approaches include state-space algorithms. KF [67], EKF [68], ensemble Kalman filters [69], UKF [70], PF [71], and observer-based methods [72]. The Eyring model [73] and the Weibull distribution [74] are other model-based approaches.

The space engineering field of study lacks enough literature on fault prognosis. One available literature is a model-based method proposed by Rahimi *et al.* that used KFs and PFs to forecast the RUL of RWs onboard a satellite.

This method uses the PF approach since it is the most widely applied Bayesian method in the prognostics field and has the advantage of being flexible enough to handle nonlinear systems with non-Gaussian noise [75].

On the other hand, the lack of a suitable mathematical model for the failure prediction is the leading cause of following the data-driven approach. *Data-driven* approaches utilize the sensor(s) measurements to learn the systems' trend during the processing time. Data-driven prognosis models can be classified into four methods: Regression-based methods, Probabilistic-based methods, Markov-based methods, and artificial intelligence methods. Probabilistic prognostic models consider RUL and system states as random variables. Thus, probability density distribution (PDF) is considered to predict their statistical features [76].

Knowledge-based prognosis methods can be used if the system designer completely understands the system under study. Fault prognosis using Signal processing techniques [77] and fuzzy logic methods have been reviewed in [78], belonging to the Knowledge-based prognosis category.

Another published study in the field of space engineering is a two-step prognosis method based on LSTM proposed by Islam and Rahimi. First, the system's future state is predicted by analyzing historical and current data. The next step involves predicting the future behaviour of the RW system, and parameters can indicate the degree of degradation of the system (health index) and be used to forecast the RUL [79]. The next study's objective is to forecast the RUL needed for reloading liquefied natural gas tanks, which is crucial for ensuring the satellite plants' health and maintenance. Escobet *et al.* proposed two methods to estimate the remaining time before supplying the plant tank. One method is fuzzy inductive reasoning (FIR), a nonlinear technique based on fuzzy inference. The second is a linear process based on a double-aliasing filter. Unlike the second approach, the FIR method always predicts the RUL in a repetitively decreasing manner [80].

Combining at least two of the three main types of fault prognosis techniques leads to *hybrid* approaches. For example, a mixture of data-driven and model-based approaches is investigated in [81]. In the mentioned study [81], Baptista *et al.* used a measurement-based data-driven method to train the data and a model-based filter estimates RUL in the prediction phase. Another hybrid prognosis strategy was proposed by Sun *et al.* [82]. A combination of unscented PF and multiple kernel relevance vector machine (MKRVM) was introduced to predict RUL and the state of the health of the lithium-ion battery [82]. In [83], hybrid prognostic approaches for forecasting RUL of engineered systems are reviewed.

The classification of reviewed literature in this section is presented in TABLE 6. This table includes the methods used in each paper and the applications for each method. As can be seen from TABLE 6, there are not many fault prognosis studies pertaining to the space systems or their actuators,

TABLE 6. Summary of fault prognosis literature.

Ref.	Method	Application
[75]	Model-Based, KF and PF	RW
[76]	Model-Based, Data-Driven, Knowledge-Based, and Hybrid	Battery, Rotating Machinery, and Safety-Critical Systems
[77]	Knowledge-Based, Signal Processing Techniques	Fuel Cell System
[78]	Knowledge-Based, Fuzzy Logic Methods	Two Tank System
[79]	Data-Driven, LSTM	RW
[80]	Data-Driven, FIR	Satellite Liquefied Natural Gas Tanks
[81]	Hybrid, KF and SVM	Aircraft Bleed Valve
[82]	Hybrid, unscented PF and MKRVM	Satellite Lithium-Ion Battery
[83]	Hybrid	Engineering Systems

even for monolithic satellites. The lack of such studies in the field requires additional work on fault prognosis and failure prediction, including determining the remaining useful life for such systems in future work.

C. FAULT DIAGNOSIS AND PROGNOSIS METHODS FOR MULTI-AGENT SYSTEMS AND SATELLITE FORMATION FLYING

MASs are used in various fields in engineering, including SFF. In recent decades, they have become increasingly popular as they are more reliable and robust than centralized systems. Practically, a fault is an unforeseen event that causes a system's performance and stability to be substantially diminished. A fault in cooperative systems can be divided into two types based on its effects: *component faults*, such as faults that happen in actuators, sensors, and node controllers, and *topology faults,* such as interaction graph edge faults [84]. Because communication links exist in cooperative systems, a fault in one agent can spread throughout the entire system and affect the entire system's performance [85]. It is therefore imperative to diagnose the faults as soon as possible. Hence, numerous research works focused on designing a system to detect the fault and prevent its propagation [86]–[88].

Beni and Shahriari-Kahkeshi investigated the problem of actuator fault detection and estimation for the linear model of a team of agents with elusive state variables [14]. The designed controller works correctly in a fault-free system, and the follower agents follow the leader output as expected. However, the problem would arise if a fault appeared at the *jth* actuator of the *ith* agent. It is crucial to detect the fault and prevent it from spreading among agents, as there are interconnected communication links between agents. Fault in one agent actuator can interrupt the information flow between that agent and its neighbours. As a result, it can degrade the performance of the whole MAS or even lead to mission failure. The network topology in this research is undirected, and considered faults in this research work

have abrupt characteristics. The proposed distributed fault detection algorithm builds a fault estimator based on relative information between agents and their neighbours to observe every agent's status and develop residual signals to detect faults. A fault estimator is also proposed to determine the strength and size of the detected defect. The proposed scheme is constructed as an LMI problem, and its stability is assessed based on the Lyapunov stability law. Finally, to confirm the acceptable performance of the proposed scheme, simulations are done for a topology consisting of four leader-follower agents, which are DC motors with actuator bias fault. Thus, the objective of this work is to design a distributed fault detection and estimation scheme to detect and estimate the actuator fault. This scheme provides information that can be used to identify failure modes, reconfigure controllers, and design fault-tolerant control systems. Compared to the previous study [14], [89] is allocated to the distributed fault estimation for the MASs problem but with a nonlinear dynamics model. MASs based on agent cooperation and coordination are capable of achieving complex goals. It is not feasible or cost-effective to create observers for specific agents most of the time. As a result, if the neighbours can estimate the fault in those nodes, the entire system can quickly and purposefully deal with it. These facts encouraged Liu *et al.* to do study [89]. This study examines how an observer designed for one agent could estimate both itself and its neighbour's faults.

The fault estimation methods used in other studies, such as [90], have produced acceptable results for estimating the faults in MASs. As a result of the proposed method in the study [90], an observer constructed in one agent using accessible output information can assess which of its neighbours may be faulty and detect its fault. The main novelty of the mentioned study is finding main agents and developing observers for them. The proposed method might be helpful when an agent cannot be detected or observed or if the computation load and costs of the mission need to be reduced. The system augmented model can be constructed using the fault as an unknown input or a system state. To calculate the gains of the observer, the system LMIs should be formulated.

Additionally, to improve the estimation, the region pole constraint is applied. In [91], Shenquan *et al.* studied the actuator fault estimation for a group of N agents using an unknown real matrix to add uncertainties to the system model. An estimation error is constructed by considering the relative output information among agents. Based on this error, a distributed observer is generated for fault estimation. A set of adjustable parameters (AP) is chosen for each agent observer to improve its performance. The gain of the distributed observer is derived from a multi-constraint design method utilizing the H_∞ method with pole placement (PP). The simulation of a network consisting of four aircraft and one air vehicle with actuator faults has proven that this approach is feasible. Similarly, in [92], Zhang *et al.* proposed a novel AP-based distributed observer for MASs faults.

Liu *et al.* studied the design of a global observer for fault detection of nonlinear MASs with time delay subjected to actuator fault and external disturbances [93]. First, an augmented system (for each agent, the state and fault vectors are augmented in the state-space model of *ith* ith agent) is obtained. A global MASs equation is derived by calculating global vectors and using the Kronecker product features. Next, a fault estimation observer is obtained by considering information from a directed communication graph. Finally, the observer gain is determined by the LMI formulation. In addition, the proposed method's performance in both the entire frequency domain and the finite frequency domain is discussed. It is essential to emphasize that in [93], both external disturbances and actuator fault signals are considered within infinite and finite frequency domains. As faults occur in the limited frequency domain, it is helpful to examine the problem of fault estimation in the restricted frequency domain.

Gong *et al.* construct an adaptive observer for linear dynamic models of MASs agents to detect the sensor faults by using local output estimation errors derived from the interaction between agents and their neighbours. It is assumed that each agent's state is unmeasurable, so the relative states are not accessible for designing observers. Instead, the output information is available by a sensor(s). Based on the Lyapunov theory, fault detection errors converge dramatically to a small adjustable region around the origin [94]. It is more critical to address sensor faults in MASs rather than component and actuator faults [95]. Since cooperation control laws usually are constructed based on the local measurements between an agent and its neighbour, the sensor malfunction negatively impacts the whole agents' network performance.

External disturbances inevitably disrupt the dynamics of individual agents in MASs by lowering the performance of fault estimation. Many researchers have focused on analysis issues to reduce the impact of disturbances on the fault estimation procedure. In order to improve MASs performance, it is practical to mitigate disturbance effects by using an unknown input observer technique, which separates disturbances from system fault. Some references assumed that disturbances could be partially decoupled because it is difficult for an unknown input observer to decouple all disturbances completely [96]. In [96], Gao *et al.* assessed a distributed fault estimation using a time-varying model of the MAS. The paper suggested method can decouple sensor faults from disturbances partially. It defines an unknown input observer for each agent to decouple disturbances as much as can be achieved and reduce the effects of disturbances that cannot be decoupled via relative information flow between neighbouring agents. Calculation of the preferable parameters of unknown input observers can be accomplished through the recursive LMIs optimization method.

Shan *et al.* [97] developed a MAS with unknown actuator faults based on a leader-follower structure. The dimensional expansion method is employed to construct the fault estimation observer for the linear model of a MAS.

The dimension expansion strategy can integrate all agents in a network into a unity system; it can be done using properties of the Kronecker product. However, there is too much data to observe when observing the entire MAS, making the strategy of observation design more complicated. The estimated state variables are not as accurate as those provided by a single system. The spectral decomposition property of symmetric matrices and coordinate changes allow a system to be divided into several separate subcomponents. Spectral decomposition is performed by using the Laplacian matrix formed by a communication network between satellites to generate independent observable components. Afterwards, the spectral decomposition combines the observers of the sub-components to create a fault estimation observer of the entire system. Bai and Wang designed an observer [98] that operates the FDI relying on local information flow in the communication graph between each satellite and its adjacent satellite, which is more feasible in extensive MASs. Utilizing this method has the advantage of reducing the number of observers needed and the computing load because the suggested FDI algorithm would only require designing N-1 observers for a MAS with N agents to satisfy the algorithm assumptions. Another advantage of using this algorithm is the practically directed network topology containing a spanning tree. Unlike most previous methods based on unknown input, observers were applied to FDI for MASs with undirected topology. Bai and Wang [99] expanded their research and applied both additive and multiplicative classes of actuator fault to the agents' system model. It means some potential types of actuator faults are considered to be investigated: loss-of-effectiveness fault, bias fault, outage fault, and stuck fault.

In [100], Zou *et al.* used a distributed architecture to analyze linear time-varying systems. Unlike other resources that rely on relative state and output information since time-varying systems are being analyzed, it may not be appropriate to use relative information. An augmented model combines local output measurements in the absence of absolute output measurements. In [100], the diagnosis of a sensor fault consists of two stages, namely the generation of residuals and their interpretation. The residual-generation stage is an optimization problem involving minimizing an indefinite quadratic function. Iterative residual generation is designed using the Krein space-Kalman filtering theory. A residual-evaluation mechanism creates an evaluation function and compares it to a threshold to detect faults. A plain yes/no logic is applied to announce the presence of the fault. One of the benefits of using the Krein space-Kalman state estimation in the residual generation stage is reducing computation load.

To the authors' knowledge, there has not been an abundance of published literature on MAS fault prognosis. A recently published paper used a neural network-based method to predict MAS state in healthy conditions and then detect and classify sensor faults. In order to detect a fault, the measurement of the sensors is compared with the predicted state of a healthy system, and the residual signal is generated. A residual-triggered fault classifier is used to determine the

TABLE 7. Fault diagnosis and prognosis for multi-agent system and satellite formation flying.

Reference	Approach	Architecture	Fault Type
[86]	Diagnosis-Data-Driven	Distributed Directed/Undirected	Sensor
[87]	Diagnosis-Model-Based	Distributed Directed	Actuator
[88]	Diagnosis-Data-Driven	Distributed Unknown	Sensor
[14]	Diagnosis-Model-Based	Distributed Undirected	Actuator
[89]	Diagnosis-Model-Based	Distributed Undirected	Actuator
[91]	Diagnosis-Model-Based	Distributed Directed	Actuator
[92]	Diagnosis-Model-Based	Distributed Directed	Actuator
[93]	Diagnosis-Model-Based	Distributed Directed	Actuator
[94]	Diagnosis-Model-Based	Distributed Directed	Sensor
[95]	Diagnosis-Model-Based	Distributed Sensor Undirected	Sensor
[96]	Diagnosis-Model-Based	Distributed Undirected	Sensor
[97]	Diagnosis-Model-Based	Distributed Undirected	Actuator
[98]	Diagnosis-Model-Based	Distributed Directed	Actuator
[99]	Diagnosis-Model-Based	Distributed Undirected	Actuator
[100]	Diagnosis-Model-Based	Distributed Undirected	Sensor
[101]	Diagnosis-Data-Driven	Distributed Unknown	Sensor
[84]	Diagnosis-Model-Based	Distributed Directed	Actuator
[102]	Diagnosis-Model-Based	Decentralized Directed	Actuator
[104]	Diagnosis-Model-Based	Distributed Undirected	Actuator
[105]	Diagnosis-Model-Based	Distributed Directed	Actuator

type of fault. This study considers zero-output, drift, and deviation faults as different types of sensor faults. The main contribution of this paper is to apply the backpropagation method to predict the state of MASs where it is not possible to access the communication information flow [101].

In recent years, FDI in SFF has been the subject of many research studies. Nemati *et al.* present a distributed strategy

for detecting, isolating, and estimating actuator(s) faults in a team of satellites [84]. To find and monitor a fault in [84], nonlinear observers are created; when the residual signal surpasses a threshold, the presence of a defect in the system is announced. The observer gains are obtained by the LMI optimization method. After detecting the actuator(s) faults, a set of nonlinear unknown input observers is designed to isolate the faulty actuator(s) employing the generalized observer scheme. The understudy paper addresses one of the major shortcomings of the LMI method, namely its insensitivity and conservativeness in determining nonlinear observers. A Lipschitz formulation is applied to all designed observers to solve this problem to make the LMI method more practical without exposing an extra computation burden. Additionally, the proposed method is robust against uncertainties. The impact of uncertainties is reduced by using the H_∞ control strategy to do this robustness. The nonlinear observers created in the mentioned research work can detect its and its adjacent satellites' fault.

An SFF illustrated with a directed interaction graph is used in [102] to propose a novel fault estimation for a nonlinear model of SFF systems with actuator fault. The incipient faults that are small and develop gradually are considered in this article. They can produce bias and disrupt nominal actuator performance. The system fault is detected by constructing a decentralized unknown input observer. The motivation for this research is that most synchronization control for SFF systems ignores actuator fault, resulting in performance degradation. Although many SFF control methodologies can resist the destructive impact of unknown fault, they can only handle limited magnitude fault effects. This drawback can be addressed by applying a suitable control scheme to detect and isolate systems' faults before propagating in the whole SFF network. Comparing the designed observer with those intended in references [84] confirms that the decentralized unknown input observer is constructed in the study [98] to estimate the unknown actuator fault in each satellite following the leader. This method does not require an adaptive fault estimation scheme, and it may lessen the demanding process of online computation.

The study in [103] shows the attitude control system (ACS) is responsible for the majority of in-orbit satellite failures compared to other satellites' subsystems (32% of the total), and gyroscopes failure is the most usual reason for these failures (17%). Motivated by these statistics, Shakouri and Assadian proposed an FDI scheme, using local measurements between neighbour satellites such as relative position [104]. Thus, it is necessary to design the FDI algorithm to determine the relative position vector between a satellite and its neighbour. The first and second derivatives of the position vector can be used to derive the relative velocity and acceleration vectors. The output functions of satellite gyroscopes are developed using the mentioned vectors. An FDI process can be performed using the output function's behaviour. By comparing the output function to the threshold,

we can figure out the gyroscope fault amplitude, and after fault detection, we can isolate the fault using the output function characteristics. Among the main benefits of this approach is that it is independent of the orbit or attitude of the follower satellite. Additionally, the satellite already has a relative distance measurement sensor, so it is unnecessary to provide another sensor to the satellite to develop this algorithm.

Based on unreliable real-time data due to disturbances and actuator faults, Azizi and Khorasani designed a distributed state estimation architecture for SFF. A logical method is proposed for estimating the state of the entire satellite topology based on a fault augmented linear model of a set of sub-observers chosen by a supervisor [105]. It was applied in a formation flight of five satellites and demonstrated exceptional performance in managing environmental and dynamical uncertainties.

TABLE 7 shows that many fault diagnosis strategies are designed for agents with undirected topology, which may not be the most practical approach for real-life applications.

In the next section, some of the insights from the reviewed literature in this paper are collected and organized to provide readers with further directions for the existing gap in this field.

VI. FUTURE WORK

A primary objective of DPHM for SFF is to increase mission reliability and safety by implementing cross-cutting technologies for improving future Earth and space observation. Some potential research directions for future studies can be listed as follows.

1) *Extending available fault diagnosis and prognosis methods:* Various fault diagnosis and prognosis strategies are suggested to maintain a single satellite in orbit, such as study [55] working on fault detection of satellites' communication systems. They could be expanded and adapted to be used by a group of satellites that work together cooperatively to take advantage of using smaller satellites in constellations instead of a heavier single satellite.

2) *Applying MASs fault detection methods to SFF:* In this paper, various types of fault detection and estimation methods for MASs are discussed, such as [92] that can be applied to small satellites in the constellation as agents, by consideration of each satellite's formation variables in the MASs control law [13].

3) *SFF fault prognosis:* There are few works on the fault prognosis of single satellite systems [75]. So, as expected, there is a lack of research on MASs and SFF fault prognosis that should be noted in the future.

4) *Adaptivity and robustness of estimation methods:* Many issues remain with implementing nonlinear filters that ensure adaptivity, robustness, and minimal estimation error covariance [75]. With increasing knowledge of nonlinear filtering techniques and technology to cope with the computational demands of these algorithms,

better estimations and posterior distributions should be possible. Additionally, complex nonlinear dynamic models may have high dimensionality and simultaneously estimate both parameters and states.

5) *Improving the existing methods to be more feasible:* As shown in TABLE 7, many fault diagnosis strategies are designed for agents with undirected topology. To be more practical, these works can be extended for use in SFF with a directed communication graph and more communication limitations, such as unmodeled dynamics, packet loss, and time delays [39]. Besides, several fault diagnosis methods are applied to time-invariant or static topologies. It seems more realistic to apply it to a dynamic or time-varying communication graph [58]. In addition, additive faults are usually considered in the systems in the reviewed literature. It can be extended to include both additive and multiplicative fault. Also, various fault types should be considered [99].

6) *Improving decoupling methods:* SFF should be able to address the shortcoming of comprehensive decoupling (not only partially) of environmental disturbances from fault estimation errors [96].

7) *Enhancing the rate of fault diagnosis:* The rate of fault diagnosis is also an essential factor for future fault diagnosis strategies [88].

8) *Using a stochastic estimation method:* Many fault diagnosis strategies are designed using the deterministic method. It means they ignore the effect of systematic and environmental uncertainties on the model behaviour. So that, the result is not feasible. Instead, these research works can consider the uncertainties and use a stochastic estimation method [89].

9) *Employing a hybrid method:* The problem of fault diagnosis and prognosis of SFF is complex and challenging. Using a hybrid method can help the designer find the best solution to minimize the cost function without reducing accuracy [83].

VII. CONCLUSION

This paper provides an overview of the latest research and development on fault diagnosis and prognosis schemes for a single agent and a team of agents working together, emphasizing on small satellites in constellation. Moreover, some key concepts related to diagnostic and prognostic approaches are also described. This review identifies and categorizes the literature on various schemes, including model-based, data-driven, knowledge-based, and hybrid. However, as a result of this review paper, we can conclude that satellite formation flying fault diagnosis and prognosis have many challenges and shortcomings that need to be addressed in future.

Some of these challenges are listed in the following section to provide future directions for the research and researchers working in this field.

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