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Spacecraft fault detection and identification techniques using artificial intelligence

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Spacecraft fault detection and identification techniques using artificial intelligence

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Abstract

The complexity of spacecraft systems and their missions is increasing, requiring higher levels of performance and innovative solutions. It is essential to have onboard autonomy with minimal faults to ensure reliability, availability, and safety. Fault Detection and Identification (FDI) is critical in identifying spacecraft faults before they cause major failures. However, FDI design and application are challenging due to the space environment and the reliance on system information. To improve accuracy, speed, and noise robustness, modern FDI methods based on Artificial Intelligence (AI) techniques have been developed. This paper investigates the latest FDI techniques in the spacecraft attitude determination and control subsystem (ADCS) and electrical power subsystem (EPS). The article discusses various FDI methodologies and frameworks, highlighting their advantages, drawbacks, and the significance of AI implementation. Additionally, the paper presents a thorough analysis and comparison of the different methods.

1. Introduction

Spacecraft is considered one of the most expensive control systems created in recent decades. It consists of a group of integrated systems such as EPS, ADCS, onboard computer (OBC), thermal control system (TCS) and communication system (CS). To ensure quick and precise execution of tasks in a real-time environment, spacecraft must maintain a high level of efficiency. Failures in any spacecraft subsystems will significantly harm the mission's chances of success.

According to statistics in 2009 [1], 130 different on-orbit spacecraft had been lost in space before reaching the end of their lifetime, with 156 recorded failures. This study shows that most frequently failures occurred in spacecraft were conducted as a result of ADCS and followed by EPS failures. Increasing operational demands on autonomous spacecraft systems require structural methods to support the design of a complete and reliable monitoring system.

To improve the reliability and availability while providing a desirable performance, it is necessary to design control systems with fault-tolerant control (FTC) capability, while potential faults are tolerated [2]. These types of control systems are often known as fault-tolerant control systems (FTCS). There are two main approaches to design techniques for FTC: passive and active. Passive FTC involves designing a controller that can handle a predetermined number of known faults without needing online information about faults. This type of controller is relatively simple to implement and can mitigate expected faults. However, it has limited fault tolerance capacity and certain characteristics that make it less effective in dealing with faults. Thankfully, active FTC offers a solution by utilizing available resources and incorporating redundancy in both physical and analytical systems to handle unforeseen faults [2]. A general diagram for active FTC is illustrated in figure (1).

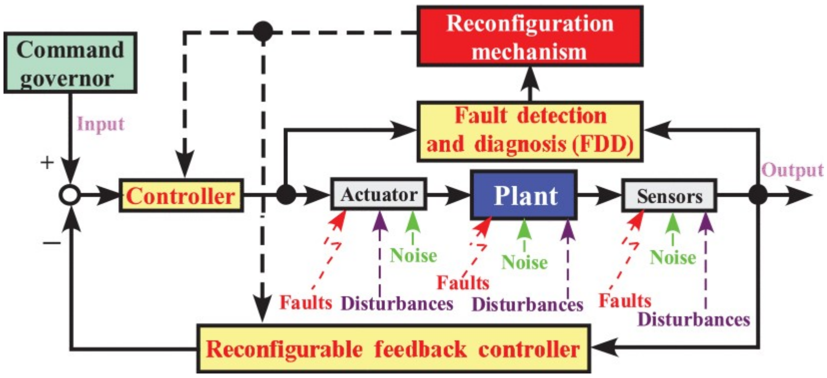


Figure 1: Schematic diagram for active FTC systems [2].

Active FTC addresses faults by either choosing a pre-established control action or generating a new control action in real-time. In both cases, an FDI algorithm is necessary to constantly update information about the system's status and any induced changes, and to adjust the control law as needed. In this context, FDI systems provide basic information about system health status and enable subsequent tuning actions to improve system reliability, availability and conveniently [3].

FDI techniques designed for ADCS or other spacecraft systems is typically comprised of three stages. Initially, fault detection is implemented to recognize any faults that may arise. Following that, a fault isolation mechanism is established to determine the type and location of the fault, along with identifying the component experiencing the fault. Finally, fault diagnosis or identification is conducted to obtain the magnitude or value of the detected fault.

S. Yin *et al* (2016), introduced in [4] an intensive review with a refined classification for the existing FDI techniques that are being applied in space systems, and he categorized these techniques into two classes: model-based and data driven-based FDI. A refined classification of the existing FDI techniques is shown in figure (2).

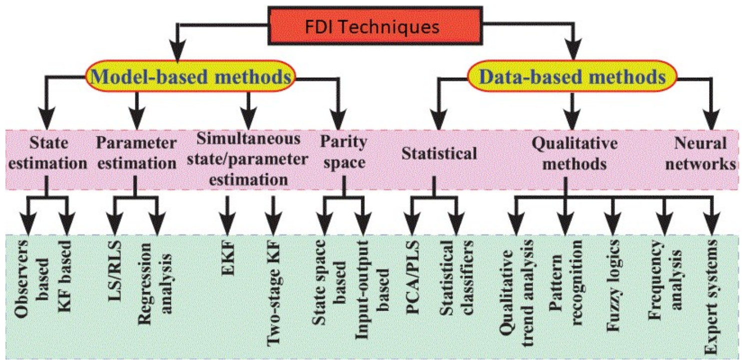


Figure 2: Classification of FDI techniques for spacecraft systems [2].

Model-based techniques rely on modeling capabilities to identify and diagnose faults in spacecraft subsystems. However, the growing complexity of these subsystems has impacted the availability and accuracy of mathematical models, which has limited the use of model-based FDI. The typical structure of FDI model-based involves two stages, as depicted in figure (3): (1) a residual generator, which is a filter designed to generate non-zero residual signals when a failure occurs, and (2) a decision-making process that distinguishes between genuine failures and false alarms caused by noise or other disturbances. The decision-making process can involve simple threshold tests, or it may use a statistical method [5]. Typically, the fault information obtained from this monitoring module is then utilized to actively modify the controller, ensuring that stability and acceptable performance of the entire system are still maintained.

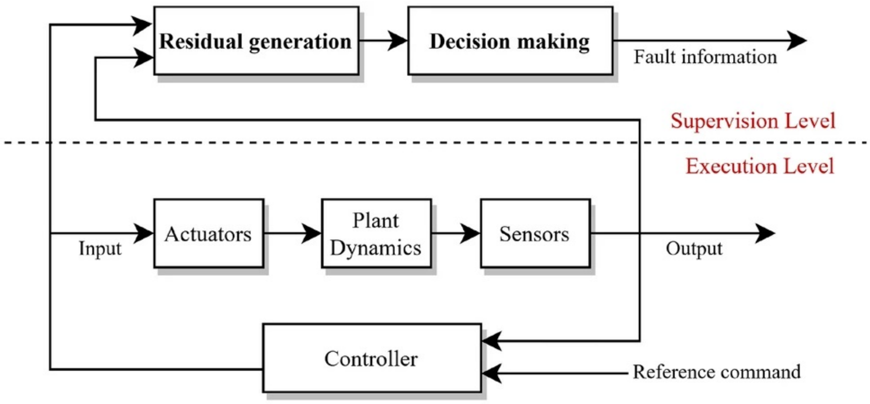


Figure 3: General architecture of a model-based FDI system [5].

Data-driven technique uses empirical data, rather than prior assumptions or theoretical models, to guide the decision-making process. In these techniques, data is used as the main source of information and the basis for making predictions or decisions. Data-driven techniques are getting more attention by the recent researchers as it offers various benefits such as minimal memory consumption, ease of use, and quick execution time [6]. These aspects greatly affect the resources of the spacecraft's OBC such as, microprocessor, non-volatile memories, volatile memories and different peripherals. Comparison between set of data-driven and model-based techniques using memory benchmark illustrated in tabble(1) showing the impact of using data-riven techniques on memory utilization.

Table 1: Memory benchmarks [6].

Technique	Reaction Wheel		Solar Panel	
	Memory (Kbyte)	Memory utilization %	Memory (Kbyte)	Memory utilization %
ARMA	122	6.7 %	223	11.1%
Prony	18	0.9%	30	1.5%
STE-Prony	12	0.6%	21	1.05%

The performance comparison for different data-driven techniques is summarised in table (2). As shown in table (2), no technique outperforms the other on all performance metrics. Taking an examples of this, the bayesian conditional generative adversarial network in [7], which showed the best performance as it has four stars (highest grade) in classification speed,physical explanation and robustness to parameters and one star (lowest grade) in accuracy in general. A deep bayesian neural network and hybridizations with fuzzy logic are additional options that have not yet been extensively researched for FDI [8]. Application of a deep belief network (DBN), which effectively makes use of stacked boltzmann machines and a layer-by-layer learning algorithm, is another new advancement. Exploring deep learning technique for FDI showed promising results. However, it has mainly been relegated to uses outside of space applications or concentrated on a single component [9].

Table 2: Performance Comparison of FDI Data-Driven techniques [10].

	Naive Bayes	Deep Learning	SVM	K-NN	ANN
Robustness to parameters	****	**	*	***	*
Classification speed	****	**	****	*	****
Physical explanation	****	*	*	***	*
Over Fitting Handling	***	***	**	***	*
General Accuracy	*	****	****	**	***
Robustness to noise	***	****	**	*	**

This study investigates the use of FDI in spacecraft, its impact on the level of autonomy and mission success, as well as, the benefits of using different AI techniques. The latest state-of-the-art FDI techniques are presented and evaluated. Furthermore, a detailed comparison of different techniques is also discussed.

2. FDI State-Of-The art techniques

This section will showcase various FDI techniques, including those based on models and data. While model-based techniques still deliver satisfactory performance, recent researchers have shown more interest in data-driven techniques due to their promising results. Nonetheless, as demonstrated later, model-based techniques are still in use and achieving acceptable performance.

2.1. Artificial Neural Network (ANN) Model-Based FDI technique

Spacecraft actuators suffer from various types of faults such as, stuck at low, stuck at high, producing incorrect output, or may become completely faulted. ANN model-based FDI techniques used to detect faults in spacecraft actuators such as reaction wheel(RW). To create a model-based for detecting faults in reaction wheels an ANN architecture is built using MATLAB Simulink toolbox. It is selected to be a three-layered Elman network with back-propagation algorithm with two inputs and one output. Elman network output response after training phase is compared to the output response of reaction wheel dynamic model at the same inputs in fault-free normal conditions. Then, the difference between estimated and actual torque values used to generate threshold and residual for FDI task. [11–16].

FDI strategy is based on the comparison between normal threshold and fault residuals. If residual signals at any time exceeds upper or lower band of normal threshold, faulty condition is detected. To evaluate the performance of this FDI technique, dataset consists of 100 samples for each anomaly were simulated and checked by the FDI technique. Results obtained by the model based FDI approach presented in table (3) showed fault detection accuracy between (90-98)% and detection time between (270-318) m sec.

However, this approach introduced fault detection method with detection accuracy that is not meet satisfaction and reliability in fault classification, furthermore detection time is considered to be high with respect to real time onboard software computational cycle.

Table 3: ANN Model-Based FDI technique performance [17].

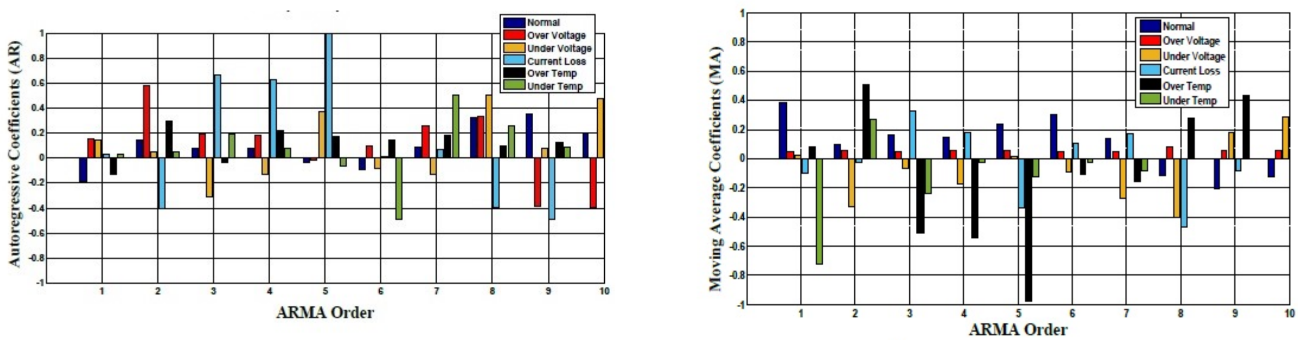
Fault Type	Detection Accuracy	Detection Time (m sec)
Over Voltage	92%	300
Under Voltage	90%	290
Current Loss	94%	301
Over Temperature	96%	318
Under Temperature	98%	270

2.2. The Autoregressive Moving Average (ARMA) Model-Based FDI technique

ARMA is described as an analysis model for time-series that typically contains two basic parts, the (AR-part) and (MA-part). The (AR-part) represents an auto-regression process for the variable values. Whereas the moving average (MA-part) introduces the error modeling term as linear combinations of contemporaneously occurring errors at previous time intervals. This general method is described berifly in [18]. Modeling of ARMA(p, q) can be performed by combining AR(p) and MA(q) models where (p) is autoregressive model's order and (q) is moving average model's order. The mathematical representation of the output parameters obtained by applying$ARMA_{p,q}(y_t)$ on a time signal y_t were expressed by equation (1) and illustrated by figures (4a) and (4b) [18] for reaction wheel torque signals up to the 10th order, the result of equation (1) [18] can be represented by two feature vectors.

$$ARMA_{p,q}(y_t) = \begin{vmatrix} AR_1 & MA_1 \\ AR_2 & MA_2 \\ . & . \\ . & . \\ AR_p & MA_q \end{vmatrix} \tag{1}$$

Where: AR(p) is AR-Model parameters for (i = 1, 2,... p), MA(q) is MA-Model parameters for (j = 1, 2,... q) and y_t is Time series actual value.



(a) 10th order AR-model for reaction wheel signals.

(b) 10th order MA-model for reaction wheel signals.

Figure 4: 10th order ARMA-model for reaction wheel signals [18].

The selection of ARMA model order has a direct impact on the distinctness of features used for fault classification. It is essential to estimate the optimal order that enables ARMA model and pre-processing algorithm to produce different data vectors for each fault.

Results in table (4) illustrate that the 10th order of ARMA model is the minimum order that provides distinct features all types of anomalies.

Table 4: Fault ID at ARMA 10th order [18].

Fault Type	Order Index									
	1	2	3	4	5	6	7	8	9	10
Voltage above limit	0	1	0	0	0	0	0	0	1	0
Voltage loss	0	1	0	0	0	0	1	0	0	0
Voltage below limit	0	1	0	0	0	0	0	0	0	1
Current Loss	0	0	0	1	0	0	0	1	0	0
Temp. above limit	0	0	1	0	1	0	0	0	0	0
Temp. below limit	1	0	0	0	0	0	1	0	0	0
Normal State	1	0	0	0	0	0	0	0	1	0

Fault classification is performed by employing an ANN classifier based on the feed-forward structure implemented using MATLAB-Simulink toolbox. General structure block diagram of ARMA model-based FDI technique shown in figure (5).

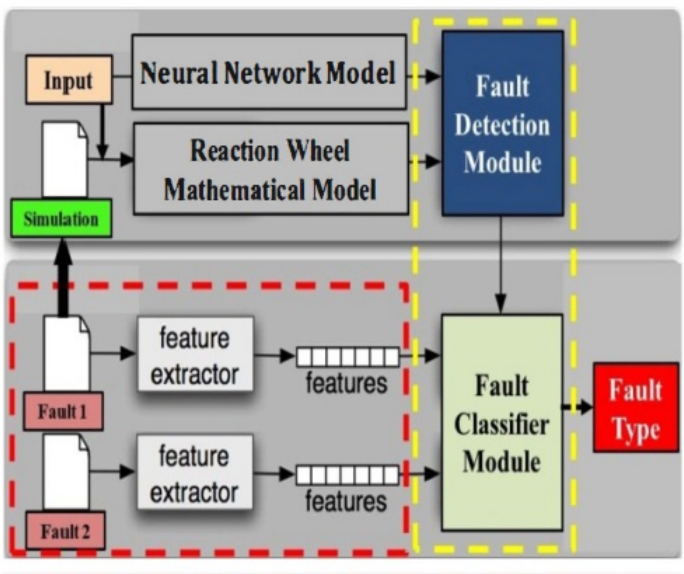


Figure 5: General architecture of ARMA model-based FDI system [6].

Learning phase was performed using 70% of features obtained by ARMA model 30% of data were left for testing and validation. FFNN architectures were evaluated by comparing classification accuracies using single layer architecture and double layer architecture at different numbers of hidden neurons as shown in tables(5).

Hence, this technique presents high classification accuracy. However, it requires a large memory footprint and more processing time that is not compatible with onboard computer requirements.

Table 5: FFNN performance using ARMA model [18].

Layer	Neurons	Reaction Wheel		Solar Panel	
		Epochs	Acc. %	Epochs	Acc .%
Single Hidden Layer	32	430	97 %	680	96%
	42	510	98%	760	97%
	52	590	99%	890	98%
Double Hidden Layer	32	800	98%	1414	98%
	42	1050	99%	1922	98%
	52	1240	99%	2500	99%

2.3. Prony Method Data-driven-Based FDI technique

Omran and Murtada in [15, 19] proposed an accurate and efficient technique for FDI for on-orbit satellites and spacecraft subsystems in real time. They proposed an approach capable of differentiating among signatures of faults that frequently take place in ADCS and EPS. This approach is developed using a feature-extraction technique employed by Prony method [20] in order to discriminate between different behaviors of spacecraft subsystems accompanied by a Feed-Forward Neural Networks (FFNN) to be used for fault classification.

To perform Prony feature extraction technique, a datasets consist of 100 samples for each fault were generated in the interval $[-50^o, 50^o]$ with a step of 1^o using reaction wheel mathematical model and 100 samples were generated using MATLAB-Simulink simulator, also for each fault of PV solar arrays within a range of $[1000W/m^2, 1300W/m^2]$ with a step of $3W/m^2$. Prony method is applied on these datasets according to equation (2) [19] at different orders starting from 2nd order up to 10th order to generate feature vectors in terms of poles and zeros as follows:

$$Prony_{(l,m)}(y_t) = \begin{vmatrix} P_{11} & P_{21} & . & P_{n1} \\ P_{11} & P_{21} & . & P_{n1} \\ . & . & . & . \\ . & . & . & . \\ P_{11} & P_{21} & . & P_{n1} \\ Z_{11} & Z_{21} & . & Z_{n1} \\ Z_{12} & Z_{22} & . & Z_{n2} \\ . & . & . & . \\ . & . & . & . \\ Z_{1m} & Z_{2m} & . & Z_{nm} \end{vmatrix} \tag{2}$$

Where: l is number of poles, m is number of zeros, n is number of data samples, P is pole value and Z is zero value.

The Prony technique for fault classification is performed by employing an artificial neural network classifier based on the feed-forward structure type implemented using MATLAB-Simulink toolbox. Learning phase was performed using 70% of features obtained by Prony' method and 30% of data were left for testing and validation. FFNN architectures were evaluated by comparing classification accuracies using single layer architecture and double layer architecture at different numbers of hidden neurons as shown in table (6). FFNN classification accuracy for reaction wheel faults and solar arrays faults respectively through the confusion matrix illustrated in figures (6a) and (6b). As shown in table (6), using single FFNN layer classifier with less number of neurons produced better accuracy than using higher number

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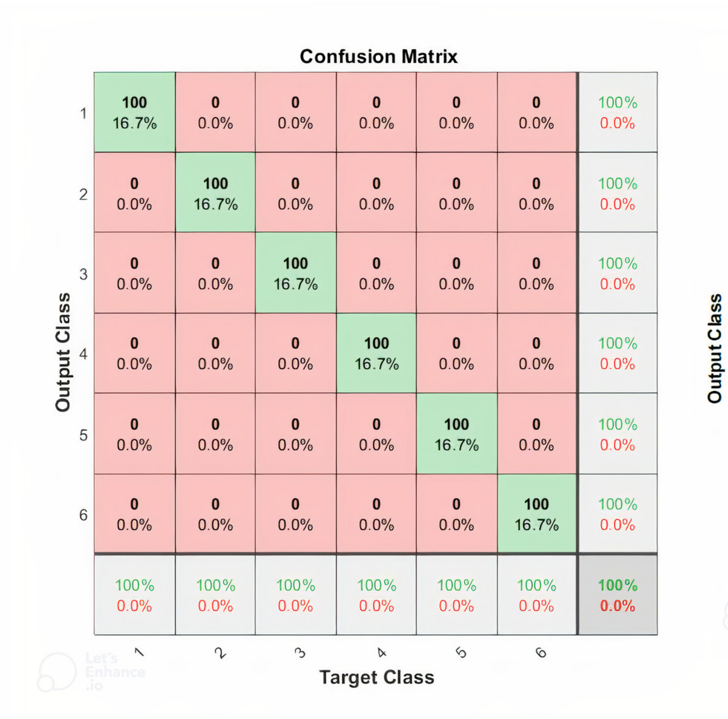
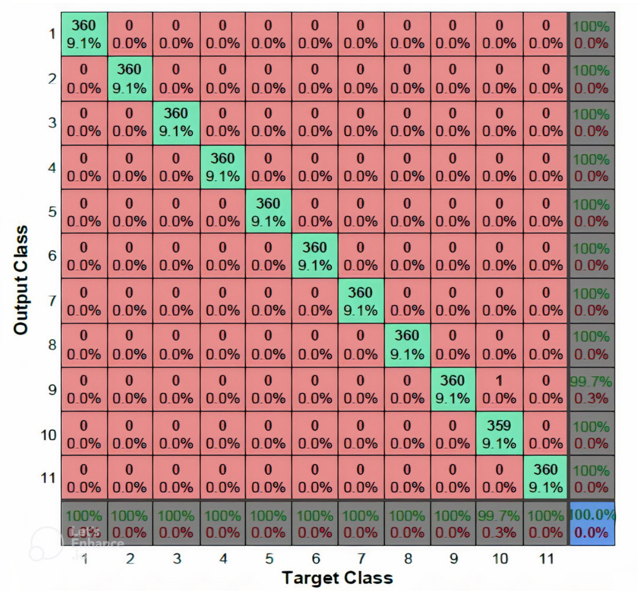
of neurons, while using FFNN classifier with double layer improves the accuracy however, the execution time increased as a result of increased iterations. Results show that Prony FDI technique has significantly greater capability than contemporary feature extraction-based research in terms of classification accuracy and complexity. Additionally, the FDI system's computation time produces quick and precise results.

Table 6: FFNN performance using Prony method [19].

Layer	Neurons	Reaction Wheel		Solar Panel	
		Epochs	Acc. %	Epochs	Acc .%
Single Hidden Layer	32	430	97 %	680	96%
	42	380	100%	500	100%
	52	560	100%	713	100%
Double Hidden Layer	32	800	98%	1414	98%
	42	840	100%	902	100%
	52	1065	100%	1147	100%



(a) Reaction wheel Faults [19].



(b) Solar arrays faults [19].

Figure 6: Confusion matrix for reaction wheel and solar arrays faults.

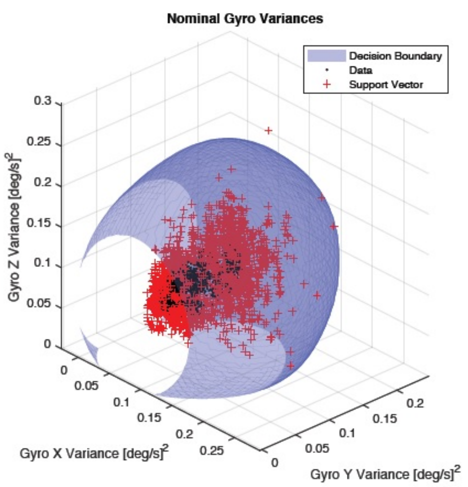
2.4. Deep Learning Data-driven-Based FDI techniques

S.P.M. (Sander) Voss in [10] developed a new FDI technique based on using Long Short-Term Memory (LSTM) network. The MATLAB-Simulink simulator of PROBA-V spacecraft by ESA [21] was used in the simulation for the case study. The proposed FDI technique concentrate on ADCS system devicses such as, star trackers and reaction wheel.

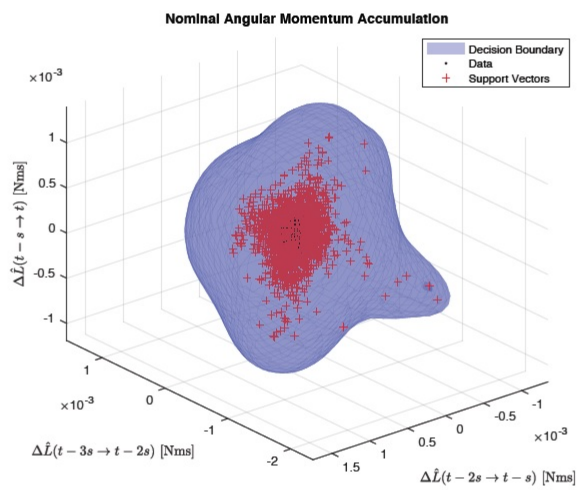
A simulation model and case study have been constructed to investigate the LSTM network, which has been identified as a promising technique. A total of 4,000 simulations, or more than 30 hours of simulation, have been performed on 35 different fault scenarios, each of which was run 90 times for the training dataset and 30 times for the testing dataset. The results showed a average performance with a blatant bias towards freezing fault prediction. It performs well when dealing with RW freeze and power outages faults identification with accuracy 80% and 95% respectively.

J Mansell in [22] developed a data-driven architecture that uses transfer learning to identify anomaly patterns from a spacecraft MATLAB-Simulink simulator and apply this knowledge to isolate and recover from faults on the real spacecraft. The method was demonstrated on the full FDI cycle for ADCS faults in a generic CubeSat simulation and used to diagnose both known and previously unknown faults on the LightSail 2 solar sail spacecraft. The core idea is to make both simulated and actual faults look identical from the perspective of fault identification. A set of one class support vector machines (OCSVMs) and rule-based checks are used to process raw telemetry into a more abstract collection of anomaly scores.

Figure (7a) shows the resulting OCSVM decision boundary with an outlier fraction of μ= 0.001. The OCSVM includes 1983 support vectors. Figure (7b) shows the resulting OCSVM. As with the other OCSVMs, an outlier fraction of $\mu = 0.001$ is used. There are 3820 total data points and 1914 support vectors. Results in figure (8) is the reliability with which nominal cases are diagnosed. Out of 22 nominal cases, all were correctly identified by the LSTM network as being devoid of faults. The method attained an overall fault identification accuracy of 96% on the ADCS simulator and 91% when applied to LightSail 2.



(a) Detecting anomalies [19].



(b) Detecting anomalies in the accumulation [19].

Figure 7: OCSVM for detecting anomalies.

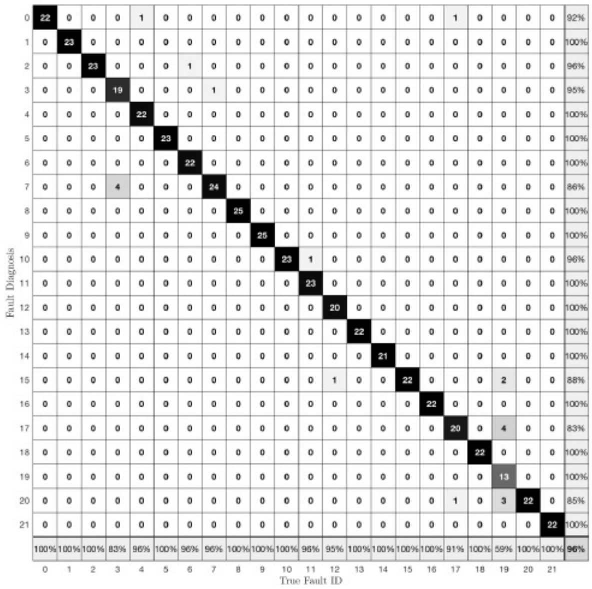


Figure 8: CM summarise LSTM fault identification performance using the fault simulator [22].

2.5. Hybrid Data-driven-Based FDI technique

Hybrid approaches were also presented for spacecraft subsystems FDI in order to enhance fault detection and classification performance.

In [23] a parameter reduction algorithm using hybrid voting mechanism (HVM) combined with SVM. (HVM-SVM) was used to improve SVM classification accuracy for spacecraft fault diagnosis. SVM adequate for tiny samples classification but not numerous faults. In this technique to handle numerous faults, several SVM classifiers were merged using the majority vote rule.multiple SVM classifiers combined and the majority vote rule used to deal with multiple faults. The contribution is not only that combined classifiers are used to vote, but also the fault associativity is added to improve the voting. Various experimental findings demonstrated the (HVM-SVM) technique's suitability for spacecraft fault identification and its superior performance when compared to other classification techniques.

A powerful technique for spacecraft ADCS has been proved using (SVM) combined with principal component analysis (PCA), which was introduced in [24]. Input data are converted to a low-dimensional feature vector using PCA to extract features. Binary (SVM) then used by the algorithm to find any faults. Multi-class SVM is used to determine the type of fault if it is found. According to experimental data the technique found to be effective and feasible for fault detection and diagnosis of spacecraft systems. However, PCA is a linear technique and is not suitable for nonlinear systems. Some components of spacecraft systems are nonlinear. Another work planned to replace PCA with nonlinear PCA, such as KPCA, for feature extraction.

3. Results analysis, open challenges and promising direction

In this section a comparison between various discussed FDI techniques were held, taking under consideration ADCS and EPS for comparison.

For spacecraft RW fault detection and identification, FDI approaches results were compared such as the model-based technique in [12,15] that introduce about 97% accuracy for classification. However, this approach introduced fault detection accuracy that does not meet satisfaction and reliability in space field, furthermore detection time is considered to be high with respect to real time onboard software computational cycle. The same presented anomalies and feature-based techniques such as (SVM with PCA) [24] that introduced accuracy up to 97.4% and ARMA Model-Based FDI technique in [15] produce detection and identification accuracy up to 96% and 98% respectively. Furthermore, regarding their algorithm complexity and number of features employed, the high orders of these techniques' required more processing time than other suggested techniques.

Hybrid approaches that were presented in [23] based on (HVM-SVM) and different classifiers were compared as other technique performance. Using deeplearnning appear to have a major role in near future in design and implementation of FDI techniques results from OCSVM and LSTM in [10,22] introduced promising progress. Prony with FFNN and STE-Prony with FFNN in [15] showed the most promising results from accuracy, memory usage and time consumed point of view related to others compared techniques. Results analysis survey are concluded by table (7).

Table 7: Results analysis for reaction wheel FDI approaches.

Ref. No.	FDITechnique	Accuracy		Mission/Dataset	Technique	No. Of Faults	Detection Time
		Detection	Identification				
[15]	ANN Model-based	97%	N/A	Simulated Data MATLAB-Simulink simulator	Simulink RW model for simulation and ANN for dynamic model	6	270-318 (m sec)
[24]	PCA and SVM	97.4%	N/A	Archived/Simulated satellite control system simulator	PCA to extract features and SVM to detect fault	4	N/A
[18]	ARMA and FFNN	96%	98%	EgyptSat-2 Spacecraft MATLAB-Simulink simulator	Simulink RW model for simulation and (ARMA) model for classification	6	12 (m sec)
[23]	HVM-SVM	99.8%	98%	Remote sensing real satellite telemetry	SVM for classifying small samples, and combine Multiple SVM classifiers to multiple faults	3	N/A
[15]	Prony and FFNN	100%	100%	EgyptSat-2 Spacecraft MATLAB-Simulink simulator	Prony method feature extraction mechanism	6	5 (m sec)
[10]	LSTM	91 %-96%	95%	PROBA-V Spacecraft MATLAB-Simulink simulator/real telemtry	Remote sensing satellite data	6	100 (sec) Fault fully identified
[22]	OCSVM and LSTM	91 %	96 %	LightSail-2 Spacecraft MATLAB-Simulink simulator/real telemtry	OCSVMs and rule-based checks to anomaly scores LSTM network to scores to each possible fault	5	N/A

For spacecraft electric power subsystem, a comparison for discussed FDI techniques was performed among different fault identification techniques, such as model based techniques [25,26]. Large-Scale Bayesian technique in [27] and feature extraction techniques such as PCA with SVM [28], KPCA as in [29] and the recent approaches that use PCA and Weighted Proximal Support Vector Machine WSVM as in [30]. Moreover, STE-Prony [15] FDI approach introduced the highest accuracy for anomalies classification compared to other presented techniques. Results analysis survey are concluded by table (8).

Based on the results, we discovered a strong relationship and trade-off between accuracy, number of faults to be detected and detection time. Many techniques discussed only the challenge of detecting one fault at a time, while other techniques discussed detecting multiple faults in multiple systems. However, the challenge of detecting multiple faults in the same subsystem at the same time requires more research and investigation because it is not well discussed, and also the detection accuracy still needs to be improved.

From a another perspective, as the number of ANN layers increases, so does accuracy, but at the same time, detection time also grows, creating a trade-off and contradiction between accuracy and detection time.

Table 8: Results analysis for solar arrays FDI approaches.

Ref. No.	FDI Technique	Accuracy		Mission/Dataset	Technique	No. Of Faults	Detection Time
		Detection	Identification				
[27]	Bayesian	100%	75%	Advanced Diagnostic and Prognostic Testbed (ADAPT)	Large-Scale Bayesian Networks by Composition	2	5.9 (sec)
[28]	PCA and SVM	100%	89%	Archived telemetry/Simulated satellite control system simulator	Offline FCM clustering and online SVM classifier	3	N/A
[29]	KPCA	100%	90%	Feng-Yun satellite real Satellite simulator	Kernel Principal Component Analysis	4	N/A
[30]	PCA and WPSVM	100%	93%	Simulation experimental data MATLAB-Simulink simulator	FCM clustering and WPSVM classification with PCA feature extraction	5	N/A
[18]	ARMA and FFNN	100%	100%	EgyptSat-2 Spacecraft MATLAB-Simulink simulator	Simulink SA model for simulation and (ARMA) model for classification	6	12 (m sec)
[15]	STE-Prony and FFNN	100%	100%	EgyptSat-2 Spacecraft MATLAB-Simulink simulator	Prony method feature extraction mechanism	6	5 (m sec)

Results analysis for various FDI techniques, as shown above , indicates that there is still much work to be done in order to improve the performance of detection and identification while also taking into account the spacecraft's limited resources, such as onboard memory, when designing and implementing FDI techniques.

Future work should focus on developing a new data-driven FDI technique that can simultaneously detect multiple faults, as well as applying FDI to other spacecraft subsystems. It should also use a new AI technique and pay particular attention to deep learning, which has shown promising results and is thought to be a fertile area for research.

4. Conclusion

This paper focused on state-of-the-art FDI model-based and data driven based techniques in spacecraft ADCS and EPS. The complexity of spacecraft systems made FDI a crucial aspect in defining the reliability, availability, and safety of spacecraft systems. The analysis shows that data-driven approaches are higher accuracy than model-based ones when dealing with FDI problems. It is clear from the comparison between different model based such as ANN and ARMA and data-riven techniques such as HVM-SVM and Prony that data driven based techniques have high accuracy in fault detection and identification in spacecraft ADCS. Beside that, in EPS most of the data driven based techniques used show better accuracy than model based techniques in fault detection and identification.The results shows the superiority of Prony with FFNN and STE-Prony with FFNN over all others mentioned techniques in the accuracy of detection and identification. However, challenges such as dealing with multiple faults at the same time and implementation with other spacecraft systems must be addressed using Prony method. On other hand,computational resources and memory space limitations still need to be considered in data-driven FDI.

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