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Anomaly detection in quadcopter flight: harnessing frequency domain analysis and barnacle mating optimization

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ABSTRACT

Ensuring the safety and efficiency of unmanned aerial vehicles (UAVs) requires effective fault detection and identification (FDI). Traditional multi-stage FDI methods, particularly those using residual detection layers, increase complexity and computational cost, limiting real-time applications. This study proposes a single-stage anomaly detection framework integrating barnacle mating optimization (BMO) with discrete cosine transform (DCT) for UAV fault detection. While prior research explored model-based and data-driven FDI, bio-inspired optimization techniques remain underexplored in frequency-domain analysis. This study develops a BMO-based fitness function analyzing 3rd, 5th, and 7th harmonic peaks to detect UAV anomalies. Software-in-the-Loop (SITL) simulations validate the method, achieving a 5-second optimal frame size, mean absolute percentage error (MAPE) of 0.05, and root mean square error (RMSE) of 195.52. The findings confirm that a single-stage detection framework via optimization method and frequency domain analysis is possible, making it viable for real-time UAV applications. This study bridges the gap in bio-inspired UAV fault detection, paving the way for safer and more efficient UAV operations.

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1. INTRODUCTION

The rapid advancement of unmanned aerial vehicles (UAVs), particularly quadcopters, has revolutionized various industries, including agriculture, surveillance, and logistics. However, the increasing complexity of these systems also raises concerns regarding their reliability and safety. Anomalies in flight data, often caused by factors such as mechanical failures, sensor malfunctions, or environmental influences, can lead to catastrophic failures if not detected promptly. Therefore, effective anomaly detection mechanisms are critical for ensuring the operational integrity of quadcopters [1], [2]. Fault detection and identification (FDI) in quadrotor is essential for maintaining operational safety and efficiency. Method used are model-based approach and data driven approach which uses multiple stages to acquire its results.

Among the various methods employed, model-based approaches stand out by utilizing mathematical models of the drone system. These methods include tools such as extended state observers and interval observers specifically designed for fault detection in UAVs [3]. Another innovative technique is the dynamic event-triggered H∞ optimization approach which proposes a dynamic event-triggered H∞ optimization

approach for UAV fault detection, which utilizes a variable sampling period, Riccati recursion for optimal residual evaluation, and eliminates the Zeno phenomenon, demonstrating improved fault detection accuracy and communication efficiency in both open- and closed-loop systems [3]. Long-short-term-memory (LSTM) based model-based approach has also been developed by [4], [5]. Research by Jeon *et al.* [4] propose an LSTM autoencoder-based anomaly detection method for quadcopter UAVs that learns complex features from normal flight data and assesses structural anomalies by adaptively considering UAV movement and runtime conditions, achieving improved specificity and sensitivity in detecting structural faults. Research by Zhang *et al.* [5] propose a FDI method for quadcopters based on airframe vibration signals, utilizing wavelet packet decomposition for feature extraction and an LSTM-based model for fault identification, demonstrating superior performance compared to back propagation (BP) neural networks (NNs) in detecting quadcopter blade faults. Multiple hybrid detection approches has also been done where the combination of multiple approach is combine together such as neuro-fuzzy and extended kalman to detect anomalies [6]-[8]. Research by Thanaraj *et al.* [6] proposes a hybrid FDI model that integrates an extended Kalman filter (EKF) for state estimation with an extreme learning neuro-fuzzy algorithm for multi-class classification, achieving improved computational efficiency and accuracy in detecting partial actuator faults in UAVs. Research by Hou *et al.* [7] presents a fault detection method using failure mode databases and runtime verification, leveraging historical fault data to generate fault modes, extract key safety attributes, and implement real-time monitoring for enhanced UAV reliability. Research by Asadi [8] introduces a two-stage FDI approach that employs a parity space method for generating residuals and an exponential forgetting factor recursive least square (RLS) method for fault identification, demonstrating effective rotor fault detection through real-time testbed experiments. Research by Hasan and Johansen [9] propose a model-based actuator fault diagnosis approach for multirotor UAVs, utilizing a cascade of a nonlinear Thau observer and a linearized Kalman filter (adaptive eXogenous Kalman filter, XKF) to detect, isolate, and estimate actuator faults with high accuracy.

Data driven approach has been done by numerous researchers. Research by Liang *et al.* [10] propose a data-driven fault diagnosis framework for fixed-wing UAVs (FW-UAVs), integrating shared nearest neighbor distance (SNND)-based DBSCAN for offline operation condition classification, SNND-KNN for online recognition, and a multiple condition-oriented dynamic KPCA (M-DKPCA) algorithm with weighted sliding window (WSW) denoising, which effectively improves fault detection accuracy under varying operational conditions. Research by Yao *et al.* [11] propose a data-driven fault detection approach for modular reconfigurable flying array (MRFA) using an improved deep forest (IDF) multivariate regression model, enhancing fault detection accuracy by incorporating an enhanced cascade layer structure, redesigned inter-layer loss function, and optimized hyperparameters, achieving improved accuracy (ACC) and area under the curve (AUC) scores compared to standard deep forest models. Research by Chen *et al.* [12] propose a fault diagnosis method for UAV motors using current signal data with few samples, employing a hybrid NN model combining a width learning system (WLS) and a convolutional neural network (CNN) to effectively extract features and classify faults, demonstrating superior performance in small-sample learning scenarios. Research by Baldini *et al.* [13] propose a real-time propeller fault detection method for multirotor drones using only onboard IMU data, integrating finite impulse response (FIR) filtering and sparse classifiers to minimize computational complexity, achieving increased classification accuracy while running efficiently on commercial flight controllers. Vibration analysis based FDI was also done by Cabahug and Eslamiat [14]. They propose a failure detection system for quadcopter UAVs as part of a three-step autonomous emergency landing safety framework, utilizing IMU vibration data and k-means clustering to classify UAV health states into normal, faulty, and failure categories, achieving fast and accurate mid-flight fault detection. Research by Steinhoff *et al.* [15] propose an acoustic fault diagnosis system for UAV propeller blades, utilizing an acoustic camera with 112 microphones and beamforming techniques to capture sound signatures, with a CNN-based model achieving an F1-score of 0.9962 for two-class classification, demonstrating superior fault detection accuracy compared to previous approaches that lacked robust environmental noise handling. Research by Ghazali and Rahiman [16] propose a vibration-based fault detection system for multirotor drones using artificial intelligence (AI), integrating fuzzy logic, neuro-fuzzy, and NN models to classify structural anomalies in drone arms, with results showing that while neuro-fuzzy and NN methods depend on dataset quality, fuzzy logic provides the most reliable decision-making for real-time UAV safety monitoring. Research by Galvan *et al.* [17] propose a sensor data-driven UAV anomaly detection method using a deep learning approach, integrating a hybrid CNN-LSTM architecture for sequential data analysis, achieving high accuracy in detecting UAV anomalies by effectively learning temporal patterns from sensor data. Research by Guo *et al.* [18] propose a sensor fault detection method for SUAVs that employs a classifier without negative samples, utilizing a local density-regulated optimization algorithm to enhance the robustness of one-class support vector machines (OCSVM) against outliers, effectively improving detection accuracy while minimizing the need for large training datasets.

Anomaly detection techniques in UAVs can generally be grouped into model-based, data-driven, and hybrid approaches. Model-based methods rely on mathematical representations of UAV dynamics and have been effective when the system model is well understood, but they often struggle under uncertain conditions or sensor noise [3], [9]. Data-driven methods, including deep learning and clustering algorithms, have become increasingly popular due to their adaptability and performance in complex environments [4], [10], [17]. Hybrid strategies seek to leverage the strengths of both, integrating observers with machine learning or fuzzy systems for improved accuracy and robustness [6], [16], [19]. Additionally, vibration-based anomaly detection has gained attention for its ability to detect mechanical faults such as rotor imbalance and structural looseness using signal processing techniques. Studies by Zhou *et al.* [20], Hu *et al.* [21] have demonstrated successful UAV anomaly detection using autoencoders and kernel-based models on vibration and state data. However, most of these approaches involve multi-stage pipelines that require residual generation or offline training. In contrast, the method proposed in this paper uses a single-stage framework based on bio-inspired optimization and frequency-domain harmonic analysis.

In addition to time-domain and deep learning approaches, several studies have explored frequency-domain and wavelet-based anomaly detection for UAVs. Time-domain techniques such as RMS, peak-to-peak variation, and statistical thresholds are commonly used due to their simplicity but often fail to detect recurring harmonic anomalies caused by rotor imbalance. Wavelet-based methods provide multi-resolution analysis and are effective in handling non-stationary signals, but they require careful parameter tuning and high computational cost. Common frequency-domain tools such as fast Fourier transform (FFT) and short-time Fourier transform (STFT) have also been applied for UAV fault diagnosis, especially in vibration analysis, but may suffer from limited frequency resolution or fixed window limitations. In contrast, the proposed method leverages the discrete cosine transform (DCT), which offers energy compaction and low computational overhead, making it suitable for detecting structural vibration anomalies. Furthermore, by combining DCT with barnacle mating optimization (BMO), the proposed method dynamically searches for critical frames that emphasize harmonic distortions (3rd, 5th, and 7th), without relying on fixed statistical rules or static segmentation used in traditional methods.

A notable gap in current research is that the current method needs multiple stages for the detection where some uses residual detection as its first stage. With the advancements in machine learning, multistage detection which uses residual detection layer may not be needed anymore. Besides that, there is the limited exploration of bio-inspired optimization techniques for UAV anomaly detection. While previous studies have analyzed vibration detection using methods such as genetic algorithms (GA) [22], they have not investigated using newer bio-inspired optimization techniques such as BMO in conjunction with frequency-domain analysis. Addressing this gap, our study proposes an innovative approach that integrates DCT with BMO to enhance the accuracy and efficiency of UAV fault detection without the need of a residual detection layer.

The new contribution of this paper is the FDI framework which only uses one stage which proposed a single stage end-to-end approach, leveraging frequency-domain analysis directly for anomaly detection. Besides that, this paper introduces BMO as an optimization strategy for UAV anomaly detection, specifically using DCT to extract harmonic components from quadcopter flight data, a combination not previously explored in UAV fault detection. This paper also shows a novel fitness function that systematically analyzes 3rd, 5th, and 7th harmonic peaks to establish threshold-based anomaly detection.

The preceding chapter will explain the algorithm works which start with the formulation of the fitness function which utilizes DCT for frequency analysis (subsection 2.1). After that, subsection 2.2 shows the full algorithm which includes the BMO with the inserted fitness function. Paper by Jamil *et al.* [23] which is the only paper found to proposed a similar algorithm which is a single stage FDI will be used to compare with the proposed FDI. The testing of the proposed method will use the same dataset as Jamil *et al.* [23] and the dataset description is added in subsection 2.3. The test result for determining optimum frames size and comparison result can be seen in section 3. Finally, section 4 will conclude the paper.

2. METHOD

In this research, we investigate into the interesting domain of quadcopter flight data analysis with an aim to find anomalies and draw valuable insights. Our approach combines creative methods such as software-in-the-Loop (SITL) data gathering with the unique BMO algorithm. Using these methods, we turn our attention to analysis of flight experiment quadcopter roll data. The dataset includes examples of anomalous flights which deviate from the insertion of problematic vibration.

Figure 1 shows the overall process of the proposed anomaly detection algorithm. The signal from the datasets is inserted directly into the algorithm without the need of residual generator which is extensively used in other research. The datasets used for this preliminary research is discussed in subsection 2.1. With the inputted signal, BMO will suggest a starting point to search for required anomalies. The starting point here is

the first point in the three correlated frames. The fitness function which is discussed in detail in subsection 2.2 will evaluate the three correlated frames. This will be done multiple times based on the starting point suggested by BMO. The result of the evaluation will inform BMO to suggest another starting point to conduct the evaluation. This process will be done until a predetermined requirements are met. The mention requirement is directly associated to BMO and can be seen in Table 1.

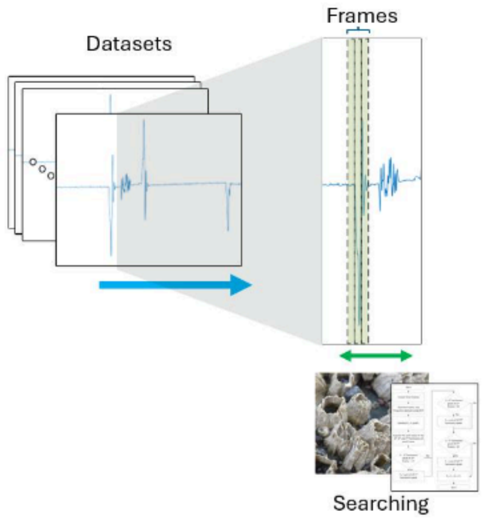

Figure 1. Overview of the proposed anomaly detection algorithm pipeline integrating BMO and DCT for evaluating harmonic peaks in UAV roll data

Table 1. Algorithm parameters

Parameters	Value
Population, Xi	30
Maximum iteration	100
pl	7

In evaluating the effectiveness of the overall algorithm, root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and detection time will be used. Besides that, the result is compared to previous research by [23] which is directly comparable to the proposed method.

2.1. Fitness function

The fitness function developed has one objective that is to find the problematic vibration based on frequency domain. The frequency domain data is based on time data in which it's translated into frequency data based on DCT [22]-[24]. The full fitness function block diagram can be seen in Figure 2.

Referring to Figure 2, the flowchart details a process for analyzing harmonics in quadrotor roll channel flight data, focusing on identifying abnormalities through systematic harmonic analysis. The process starts with data acquisition and preprocessing, where three distinct frames are created from the raw flight data. Each of these frames is then transformed into the frequency domain using the DCT, enabling a more effective analysis of the harmonic components present in the signal.

The next phase involves harmonics analysis, where each frame is examined for specific harmonic peaks. If the 3rd harmonic peak in the second frame exceeds the threshold, the sum of all 3rd harmonic peaks is calculated and stored in variable F3. This is summarized in (1):

$$F_3 = \begin{cases} p_3(y), & 1 \le p_3(y) \le 4 \\ 0, & others \end{cases} \tag{1}$$

where y is frequency domain data and p_3 is the 3rd harmonics peak value of y. The values 1 and 4 in the equations are statistically found by evaluating all 51 sets of data at the problematic vibration area.

Similarly, for the second frame, the analysis checks if the 5th harmonic peak surpasses a predetermined threshold value. If this condition is met, the sum of all 5th harmonic peaks is calculated and stored in a variable labeled F5. This is summarize in (2):

$$F_5 = \begin{cases} p_5(y), & 1 \leq p_5(y) \leq 4 \\ 0, & others \end{cases} \tag{2}$$

where y is frequency domain data and p_5 is the 5th harmonics peak value of y.

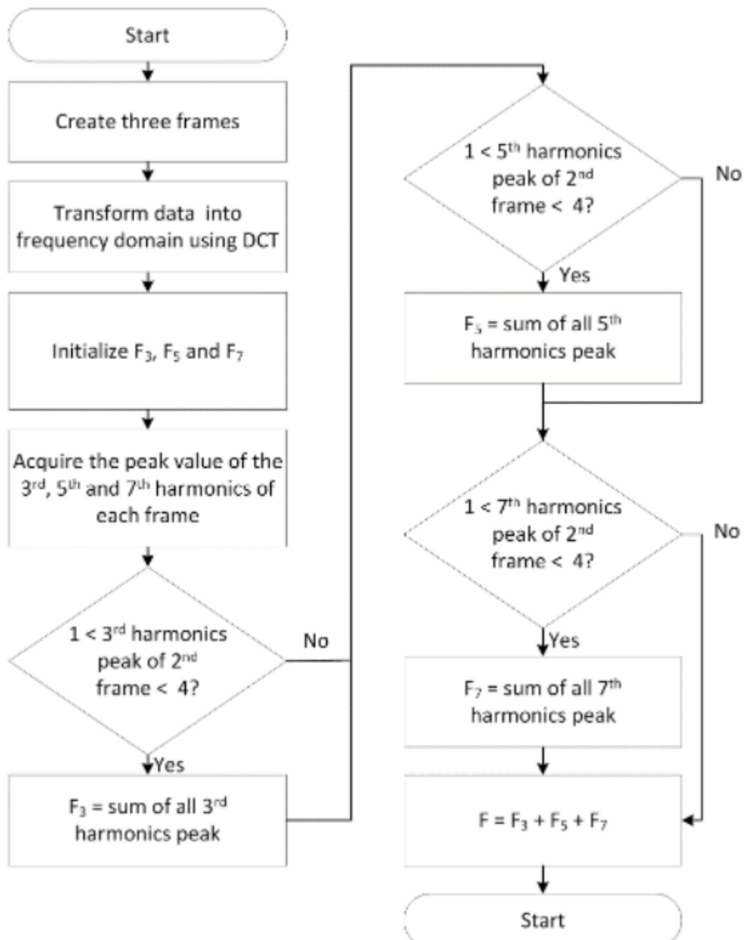

Figure 2. Flowchart of the fitness function showing the extraction and evaluation of the 3rd, 5th, and 7th harmonic peaks from three consecutive frames

Additionally, the presence of the 7th harmonic peak exceeding the same threshold is verified. If the 7th harmonic peak meets the threshold requirement, the sum of all 7th harmonic peaks is computed and stored in variable F7. This is summarized in (3):

$$F_7 = \begin{cases} p_7(y), & 1 \leq p_7(y) \leq 4 \\ 0, & others \end{cases} \tag{3}$$

where y is frequency domain data and p_7 is the 7th harmonics peak value of y.

The final step in the process is to aggregate the results. The values stored in F_3, F_5, and F_7 are combined into a single variable, F, through (4). This consolidated variable represents the overall harmonic content and is used to assess the data for any irregularities or deviations from expected patterns.

$$F = F_3 + F_5 + F_7 \tag{4}$$

In order for (4) to be used as a minimum problem fitness function, a large number is subtracted from F. In this research, the arbitrary large number (LN) is set to 30.

In this fitness function, the 3rd, 5th, and 7th harmonic components are treated with equal importance. No explicit weighting factors are applied, as all three harmonics are aggregated directly by summation. This design simplifies the fitness computation and reflects the empirical observation that all three harmonics contribute equally to the detection of structural anomalies in the UAV roll signal.

The selection of the 3rd, 5th, and 7th harmonics in the proposed fitness function is grounded from established structural vibration studies by Verbeke and Debruyne [25], who conducted a comprehensive experimental and numerical vibration analysis on a hexacopter UAV frame. Their study identified that motor–propeller units are major sources of vibration, with resonance peaks observed at specific harmonic frequencies. These harmonics, induced by propeller imbalance and structural dynamics, propagate through the UAV frame and manifest as measurable peaks in vibration spectra. Thus, selecting the 3rd, 5th, and 7th harmonics provides a practical and theoretically supported basis for capturing structural anomalies within the quadcopter roll channel using frequency-domain analysis.

To clearly define the fitness function used by the BMO algorithm, the goal is to minimize the deviation from a fixed reference value (30), which represents the expected upper bound for harmonic contributions. The complete fitness function, which forms the objective for the optimizer, is formulated as (5) and (6):

$$T = |LN - (F_3 + F_5 + F_7)| \tag{5}$$

where:
- $F_3 = \sum p_3(y)\,, if\ 1 \le p_3(y) \le 4, otherwise\ 0;$
- $F_5 = \sum p_5(y)\,, if\ 1 \le p_5(y) \le 4, otherwise\ 0;$
- $F_7 = \sum p_7(y)\,, if\ 1 \le p_7(y) \le 4, otherwise\ 0;$
- $p_n(y)$: represents the peak amplitude of the nth harmonic in the DCT transformed frame y.

This leads to the following optimization problem:

$$\min_{x \epsilon D} T(x) = \left|LN - \sum_{n\epsilon\{3,5,7\}} F_n(x)\right| \tag{6}$$

where x is the starting point of the frame in the signal, and D is the domain of valid data points in the UAV roll signal. The lower the value of T, the closer the harmonic structure is to a known abnormal condition, making it a target for anomaly scoring.

Overall, this process provides a structured approach to analyzing harmonics in quadrotor roll channel flight data. By systematically checking for specific harmonic peaks and aggregating the results, this method helps in detecting potential anomalies, which can be crucial for maintaining optimal performance and reliability in quadrotor operations.

2.2. Overall algorithm

BMO for this investigation are based on paper [26]-[28]. The full pseudocode can be seen in Algorithm 1. The algorithm starts by BMO initialization its population, maximum iterations and pl value. All the values can be seen in Table 1. Next (7) and (8) are used to determine the BMO parents [26]:

$$barnacle_d = rand\ perm(n) \tag{7}$$

$$barnalce_m = rand\ perm(n) \tag{8}$$

where $barnacle_d$ and $barnacle_m$ are mated parents and N is number of populations.

With the parents known, the child is determined based on (9) and (10). If both parents is equal to pl, (9) is used, otherwise (10) is used.

$$x_i^{N_{new}} = p x_{barnacle_d}^N + q x_{barnacle_m}^N \tag{9}$$

where p is normally distributed pseudo random number between [0,1], q=(1-p), $x_{barnacle_d}^N$ and $x_{barnacle_m}^N$ are Dad and Mum variables.

$$x_i^{N_{new}} = rand() \times x_{barnacle_m}^N \tag{10}$$

where rand()=random number [0,1].

The acquired child in BMO will act as the proposed starting point for the search in the dataset and where the fitness function starts. With the starting point found, three frames are created with each frame spans the size of frame size. For example, if the starting point proposed is 100, the first frame will occupy from point 100 until 200. The second frame will occupy from point 200 till 300 and the third frame will occupy from point 300 till 400. With these three frames, the fitness function in Figure 2 is executed until the end to find F. As mentioned in subsection 2.1, the final evaluation value (T) is the absolute value resulting from the subtraction of F to the value 30. The starting point will be saved as well as T.

The whole process from the determination of the BMO parents till finding T is repeated until the maximum iteration is reached. For every iteration, T value will be compared to previous and if current T is less than previous, the T value is updated to the new T and the new starting point will be saved. Algorithm 1 is run 50 times for each dataset to evaluate its effectiveness. The full code can be acquired by properly applying for the code via emailing corresponding author. The overall flow of the anomaly detection pipeline is illustrated in Figure 1, while the detailed procedural steps are formalized in Algorithm 1, which represents the pseudo-code implementation of the proposed method.

Algorithm 1. Algorithm pseudo-code

```
Initilize the barnacles population
Set T (the best solution) to large value
Set the value of pl
while ( I<Maximum iterations ) DO
    Selection using equations (7) and (8):
    if selection of Dad and Mum = pl
        for each variable
            Children generation using equations (9):
            end for
    else if selection of Dad and Mum >pl
        for each variable
            Children generation using equations (10):
        end for
    end if
    If the present barnacle crosses any boundaries, bring it back.

    Create consecutive three frames with the children as starting point (start of fitness function (Figure 3)
    Aquire the data from dataset which overlaps with the three frames
    Calculate fitness function based on equation (6)
    Update T If there is a better solution, Sorting and update
    I=I+1
end while
Return T
```

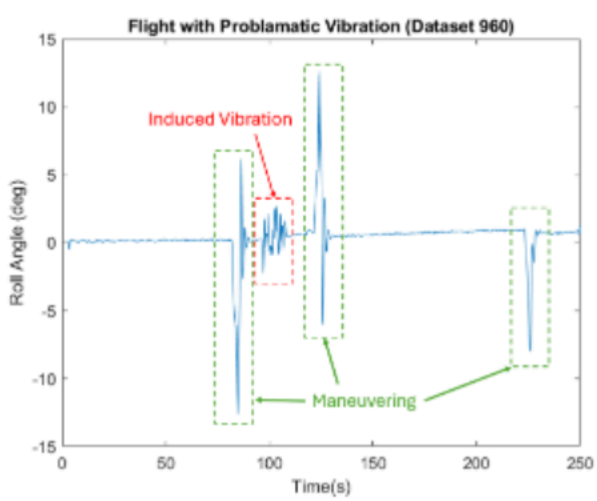

Figure 3. Example of roll angular velocity data with a marked point of induced vibration anomaly used for algorithm validation

The BMO algorithm was selected due to its strong convergence behavior and minimal parameter tuning requirements compared to other metaheuristics such as particle swarm optimization (PSO), GA, or grey wolf optimizer (GWO). BMO has demonstrated effectiveness in prior engineering applications for problems involving nonlinear fitness landscapes, as it balances exploration and exploitation through its dynamic mating and mutation-inspired mechanisms [26], [27]. Unlike PSO or GA which often require multiple hyperparameters or suffer from premature convergence, BMO's population diversity and adaptive search allow it to efficiently explore critical segments in frequency-domain data. While direct empirical comparison with other metaheuristics is beyond this study's scope, the method was benchmarked against a previous single-stage FDI method using GA [22], showing improved detection accuracy and computational consistency. These results justify BMO as a suitable optimizer for anomaly localization in UAV frequency-domain signals.

2.3. Dataset

The time-series dataset used in this study was generated using a SITL simulation framework based on ArduPilot, Mission Planner, MAVProxy, and sim_multicopter, as described in [22], [23]. This framework enables realistic emulation of quadrotor flight dynamics, including IMU, GPS, and actuator responses, while allowing safe and repeatable anomaly injection without physical UAV hardware [29].

To simulate flight anomalies, artificial vibration disturbances were introduced into the quadcopter model during mission execution. These disturbances emulate real-world faults such as rotor imbalance, structural loosening, and partial arm detachment, a common cause of irregular vibration patterns during flight. Anomalies were inserted at specific waypoints during maneuvering to test detection sensitivity under dynamic conditions.

The SITL setup realistically reflects external influences such as wind direction changes and vehicle attitude adjustments. Prior research has validated the effectiveness of SITL in simulating UAV behavior for mission testing and fault analysis [30]-[32]. This ensures that the collected data closely resembles actual flight profiles, supporting the robustness of the proposed frequency-domain detection method.

The quadrotor was flown independently using waypoint navigation within the SITL framework. To demonstrate the impact of quadrotor component failure on vibration, induced vibrations were introduced to the sensors while the vehicle was in motion. Each data set exhibited variations in vibration location and duration, alongside changing wind direction and velocity. The Mission Planner software logged attitude (roll, pitch, and yaw angular velocity) and altitude (z-axis) data.

Figure 3 illustrates an example of data collected from the roll angular velocity channel, comprising 51 data points. Notably, Figure 1 highlights a problematic vibration induced at data point 960 (marked with a red dotted line), caused by the quadcopter's varying wind velocity during maneuvers in the x-direction. Noted that the flight data also consist of maneuvering. The full dataset can be acquired by properly applying for the data via emailing corresponding author.

3. RESULTS AND DISCUSSION

This section presents the primary findings of the research, providing a detailed comparison and critical discussion of the results obtained. The implications of the findings are also interpreted to highlight their significance in the broader context of UAV fault detection. Since only a similar approach found is by Jamil *et al.* [23], the result is compared directly to it.

3.1. Fitness function performance

In order to acquire an optimal result, the frame size for the proposed method need to be determined first. Frame size in terms of second is changed from 1 second to 10 seconds with 1s incremental. Each second consists of 20 points on the dataset. Figure 4 shows the performance of Algorithm 1 in detecting the induced vibration in the quadcopter flight data in terms of MAPE and detection time with respect to the frame size. Whereas Figure 5 shows the performance in terms of RMSE and MAE of the same Algorithm 1 with respect to frame size.

Referring to Figure 4, the result shows a trade-off between accuracy and detection time. Algorithm 1 demonstrates an inverse correlation between frame size and accuracy, where smaller frame sizes (e.g., 1 s) result in higher MAPE (0.22), while larger frame sizes (e.g., 10 s) lead to longer detection times (4.81 s). This shows that smaller frame sizes do not provide adequate enough data for accuracy in detecting the anomaly. This also suggests that the 5s frame size offers the best balance between detection efficiency and computational performance. Referring also to Figure 5, the result shows that the optimal frame size is 5s which correlates with the lowest RMSE (195.52) and MAE (108.55), indicating that Algorithm 1 achieves the highest accuracy at this frame size which is coherent with the result deduced in Figure 4. Based on both results in Figures 4 and 5, it is evident for this research the use of frame size=5s gives the best performance at this frame size.

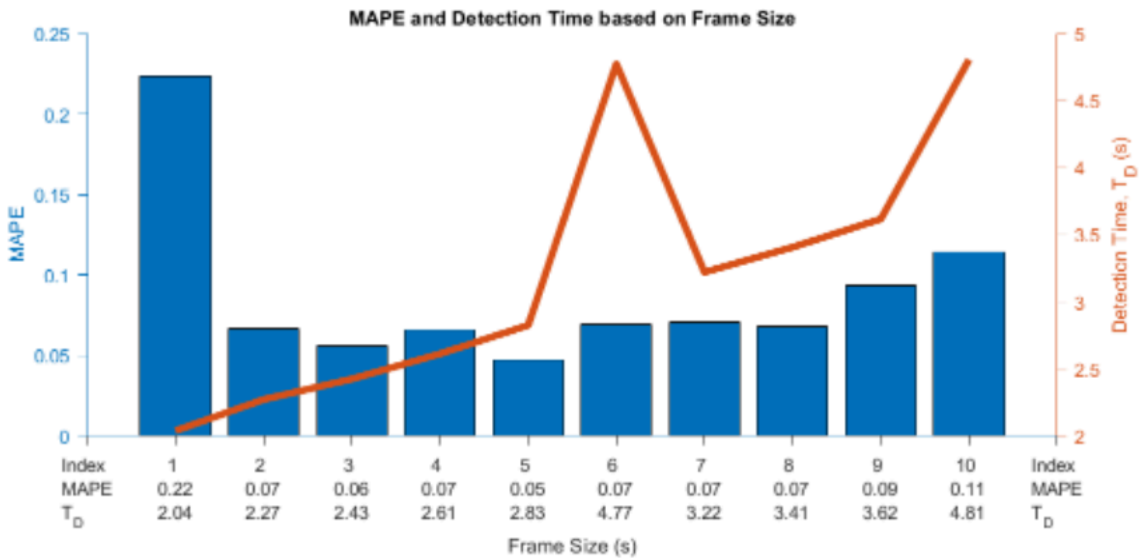

Figure 4. MAPE and detection time results for varying frame sizes, showing optimal performance at 5 seconds

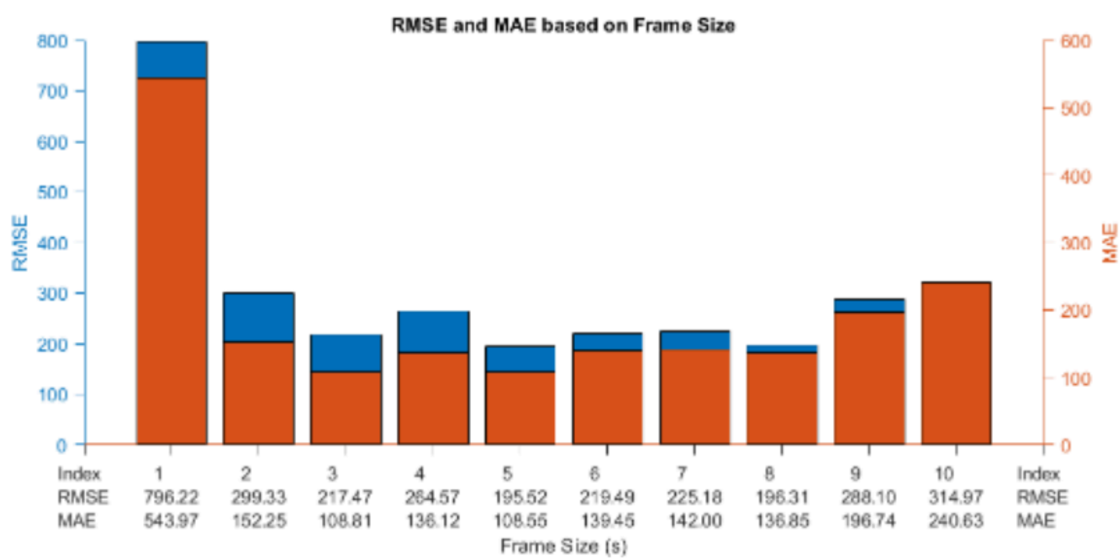

Figure 5. RMSE and MAE analysis across different frame sizes, with the best accuracy achieved at a 5-second frame size

3.2. Comparison

Since only a similar approach found in the literature is by Jamil *et al.* [23], the result is compared directly to it. The same test procedure in subchapter fitness function performance is done here. Figure 6 shows a comparative analysis of the RMSE between two methods: Algorithm 1 and the method from Jamil *et al.* [23] Algorithm 1 consistently outperforms Jamil's method for all frame sizes, as evidenced by the lower RMSE values. For instance, at a frame size of 2 seconds, Algorithm 1 achieves an RMSE of 299.33, significantly lower than Jamil's RMSE of around 446.46. This trend continues across all frame sizes, demonstrating the robustness and efficiency of Algorithm 1 in detecting anomalies.

Referring to Figure 6, the best performance of Algorithm 1 is observed at a frame size of 5 seconds, the same result that is shown in fitness function performance subchapter, where it achieves the lowest RMSE value of 195.52. In contrast, Jamil's method shows an RMSE of around 1046.31 at the same frame size, emphasizing a substantial difference in performance. The worst performance for the proposed method occurs at a frame size of 1 second, with an RMSE of approximately 796.22. These results indicate that Algorithm 1 is more effective in minimizing error and detecting induced vibrations in the flight data.

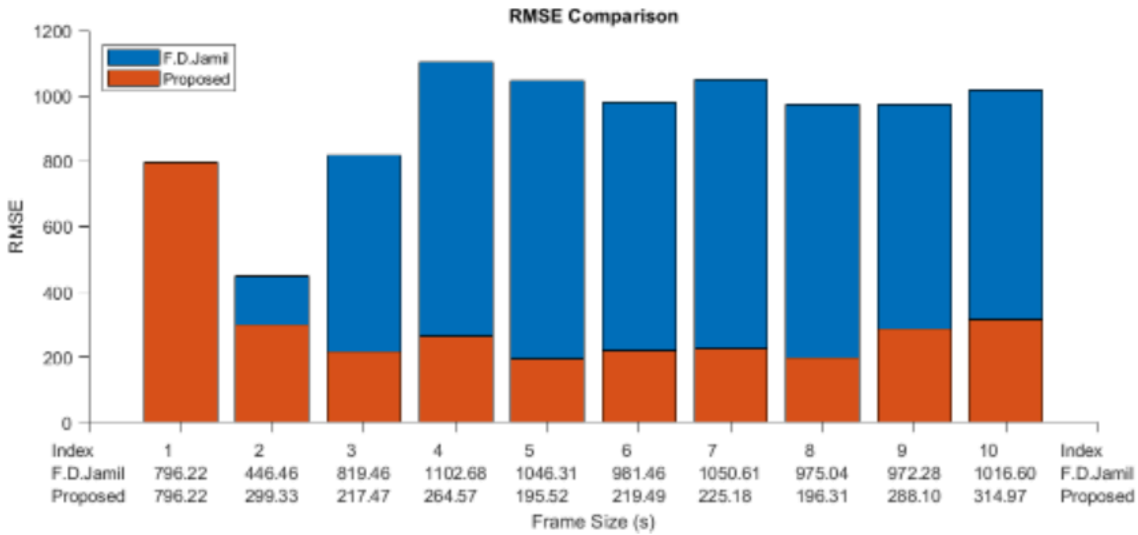

Figure 6. RMSE comparison between the proposed method and Jamil *et al* [23], highlighting consistently lower error by the proposed method

Additionally, the results suggest that Algorithm 1 is better at identifying anomalies within the quadrotor roll data. The enhanced precision in anomaly detection implies that Algorithm 1's sensitivity and adaptability are better tuned for this specific application, making it more reliable for real-time fault detection. The consistent performance across various frame sizes also suggests that Algorithm 1 is robust and can handle different data variations effectively. The substantial reduction in RMSE values underscores the proposed method's superiority as a more accurate and efficient tool for fault detection in quadrotor systems. This validates the proposed single stage end-to-end anomaly detection framework.

Figure 7 illustrates a comparative analysis of MAPE between the two methods. The result highlights the effectiveness of each method in detecting induced vibrations in quadrotor flight data. The best performance for Jamil's method is observed at a frame size of 2 seconds, with a MAPE value of 0.09. Conversely, its worst performance occurs at a frame size of 4 seconds, where the MAPE value reaches 0.40. On the other hand, Algorithm 1 demonstrates superior performance, achieving its best result at a frame size of 5 seconds with an impressively low MAPE value of 0.05. The worst performance for Algorithm 1 is at a frame size of 1 second, with a MAPE value of 0.22 which is similar to Jamil's. These numerical findings indicate that Algorithm 1 generally outperforms Jamil's method across most frame sizes, suggesting higher accuracy in anomaly detection.

Furthermore, the results show that Algorithm 1 yields lower MAPE values compared to Jamil's method, indicating better performance in detecting anomalies. The optimized frequency-domain approach significantly enhances fault detection accuracy while maintaining computational efficiency. The lower MAPE values across most frame sizes for Algorithm 1 signify its potential for maintaining UAV operational integrity and safety, making it a valuable tool for real-world applications in UAV anomaly detection. Moreover, this demonstrates the efficacy of Algorithm 1 for UAV anomaly detection, a novel contribution not previously explored in the literature.

Figure 8 presents a comparative analysis of the MAE values for the two methods. When examining the results, it is noteworthy that Jamil's method achieves its best performance at a frame size of 2 seconds, where the MAE is 218.24. For Algorithm 1, the best performance is at a frame size of 5 seconds, where the MAE is 108.55. This outcome highlights Algorithm 1's effectiveness in capturing anomalies even at the smallest time scale. Equally, the worst results appear at the 4-second frame size, where Jamil's method demonstrates a significant increase in MAE to 891.12. In contrast, Algorithm 1 maintains a markedly lower

MAE of 136.12 at the same frame size, indicating its superior performance even in less favorable conditions. Compared to the GA-based detection method proposed by Jamil *et al.* [23], the BMO-integrated system demonstrates lower RMSE and MAPE values at optimal frame sizes confirming its practical suitability in harmonic-based anomaly detection tasks.

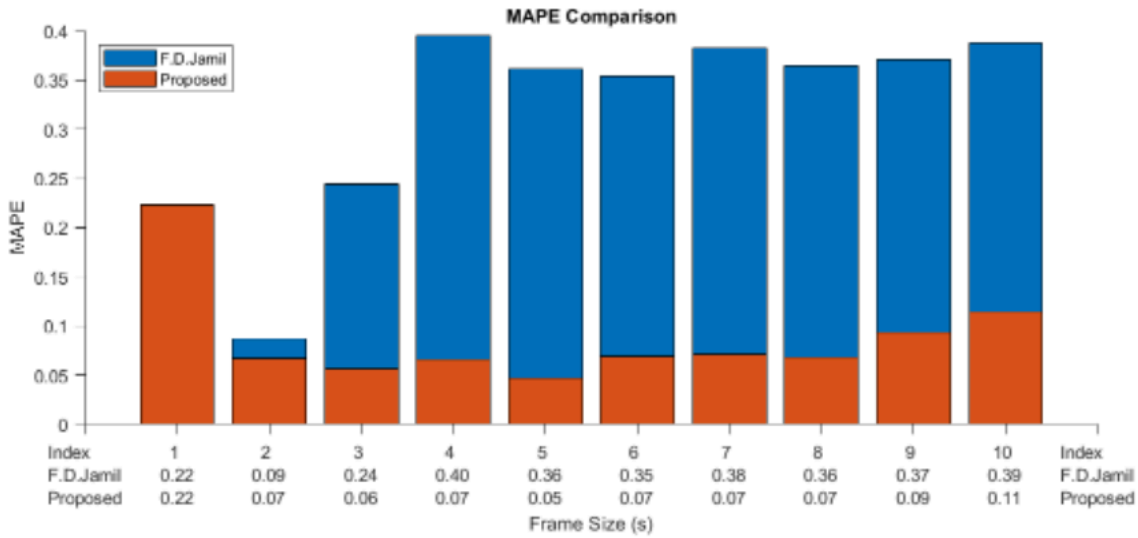

Figure 7. MAPE comparison indicating improved detection accuracy of the proposed method across most frame sizes

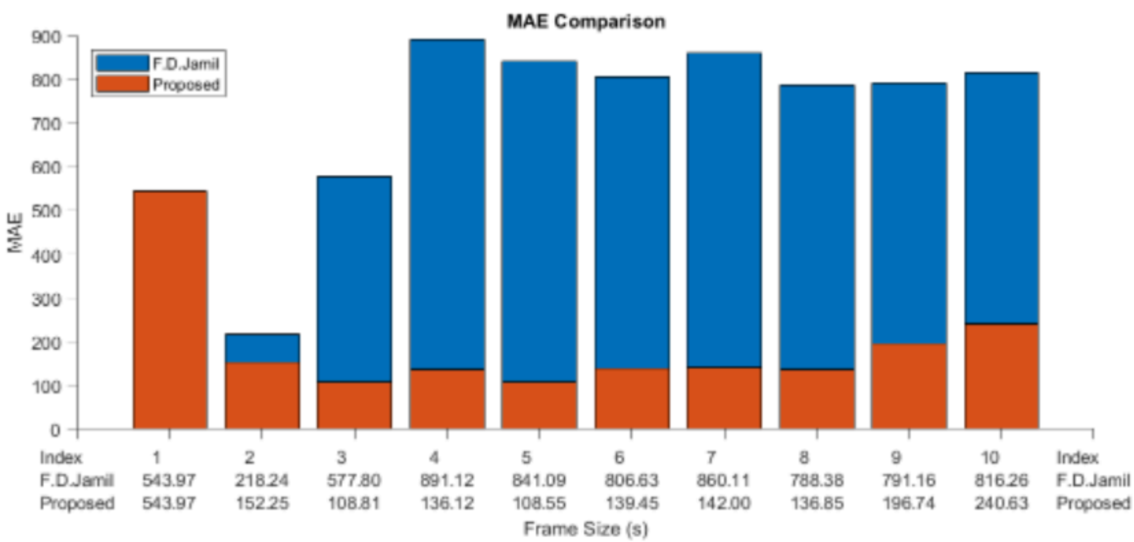

Figure 8. MAE comparison showing the proposed method's superior performance in minimizing anomaly detection error

The result also provides valuable insights into the robustness and efficiency of both methods. As frame sizes increase, a decline in performance is observed for both techniques; however, Algorithm 1 shows greater resilience against this variation. Its ability to effectively adapt to larger time frames suggests a better handling of noise and complex patterns. Additionally, the consistent outperformance of Algorithm 1 indicates fundamental differences in processing data anomalies. These findings highlight opportunities for further refinement of fault detection methodologies in UAV systems, showcasing the potential for optimizing quadrotor performance using Algorithm 1. This aligns with the research problem statement, where previous

approaches relied on multi-stage detection, while the proposed method streamlines anomaly detection into a single-stage framework with increased precision and reliability.

In addition to software-based detection methods, hardware-based anomaly detection systems—such as Kalman filters, residual generators, and IMU sensor fusion—are commonly implemented in UAVs for real-time state estimation and anomaly detection [3]. These techniques are effective in identifying sensor-level inconsistencies and navigation anomalies. However, they often rely on accurate dynamic models, are sensitive to environmental disturbances, and may struggle to detect mechanical faults such as structural vibration. The proposed frequency-domain approach based on BMO and DCT offers a complementary perspective by detecting mechanical anomalies through harmonic analysis in roll signal data. It can serve as a post-flight diagnostic tool or be integrated into onboard edge-computing modules to improve UAV safety and fault coverage, especially in detecting structural degradation not captured by traditional state estimators.

Overall, Algorithm 1 significantly improves fault detection accuracy while maintaining computational efficiency, making it a promising alternative for real-time UAV monitoring applications. These findings validate the importance of using bio-inspired optimization techniques such as BMO in conjunction with frequency-domain analysis for UAV fault detection, reinforcing the contribution of this research.

4. CONCLUSION

This study introduced a novel single-stage FDI framework for quadcopters, leveraging BMO and DCT for anomaly detection. By eliminating the need for a residual detection layer, the proposed approach streamlines the detection process while maintaining high detection accuracy and computational efficiency.

The results demonstrated that the proposed method consistently outperforms approach from the compared method. At an optimal frame size of 5 seconds, the proposed fitness function achieved the lowest MAPE of 0.05 and RMSE of 195.52, highlighting its effectiveness in accurately detecting anomalies. This research confirmed that a single-stage, end-to-end detection framework is both viable and superior in terms of precision, adaptability, and computational efficiency. The proposed method's ability to detect 3rd, 5th, and 7th harmonic peaks proved essential in identifying problematic vibrations in UAVs, reinforcing the practical applicability of frequency-domain analysis in real-world scenarios. Furthermore, the study validated that bio-inspired optimization techniques such as BMO can significantly enhance UAV fault detection, bridging the research gap in bio-inspired FDI methodologies.

Beyond simulation, the proposed anomaly detection method shows promise for real-world applications. Since it relies solely on roll channel data from onboard IMU sensors and uses lightweight computation via DCT and BMO, it is suitable for integration into embedded flight controllers. This makes it feasible for deployment in autonomous drone operations, where real-time fault detection is essential for mission safety. In drone swarms, the method can be run locally on each UAV to detect and isolate failing units, thereby increasing the robustness of distributed aerial systems. Additionally, its sensitivity to structural vibration makes it useful for predictive maintenance in industrial UAV platforms used for inspection, surveillance, or logistics. These applications highlight the potential for this method to enhance safety and reliability in both individual and coordinated UAV operations.

To enable these real-world applications, future work will involve conducting experimental validation will be conducted to complement the SITL simulation results. Additional research will explore integrating deep learning models with BMO to further improve detection robustness, while also reducing computational complexity to support real-time implementation on UAV microcontrollers and edge devices.

5. FUTURE WORKS

While this study presents a promising approach to UAV anomaly detection, several limitations remain that should be addressed in future research: i) the study relies on SITL simulations, which, while effective, do not fully capture real-world UAV operational conditions. External factors such as wind turbulence, sensor drift, and environmental noise were not explicitly tested; ii) the current method primarily detects vibration-based faults. Other fault types, including sensor malfunctions, communication errors, and power system failures, were not explored; and iii) the study focuses exclusively on quadcopter UAVs, and its applicability to other.

To further enhance the capabilities of the proposed method, future research that can be explored are: i) conducting real-world UAV experiments will help verify the practicality and robustness of the detection framework; ii) exploring hybrid methods, such as combining BMO with deep learning-based models or other evolutionary algorithms, may further enhance detection accuracy and adaptability; and iii) focus on reducing computational complexity to enable real-time onboard implementation on UAV microcontrollers and edge computing devices. By addressing these aspects, future research can extend the practical applications of this approach, making UAV operations safer and more efficient through advanced real-time fault detection systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [MFA] on request.

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