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Mobile robot replacement in multi-robot fault-tolerant formation

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ABSTRACT

Formation control in multi-robot systems (MRS) is essential for collaborative transport, environmental surveillance, material handling, and distributed monitoring. A major challenge in MRS is maintaining predefined formations or cooperative task execution when individual robots experience operational faults, potentially isolating them from the group. In mission-critical scenarios, preserving the number of operational robots is crucial for task success. To address this, we propose a Robot Replacement approach framework for differential wheeled mobile robots. This approach isolates faulty robots and dynamically replaces them with pre-deployed spares, ensuring uninterrupted formation tasks. A graph theory-based framework models inter-robot communication and formation topology, enabling decentralized coordination. The proposed techniques were implemented in a MATLAB/Simulink simulation environment. The simulated robots are equipped with LiDAR, an inertial measurement unit (IMU), and wheel encoders for navigation. Simulation results demonstrate that the framework successfully maintains the target formation and task continuity during robot failures by dynamically integrating replacements with minimal disruption.

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1. INTRODUCTION

Multi-mobile robot systems are employed across a wide range of applications, where formation control plays a crucial role in executing tasks such as surveillance, material transport, and similar operations. Each robot in such a system depends on a combination of sensors—including wheel encoders, inertial measurement units (IMU), LiDAR, GPS, and cameras for accurate localization and navigation. The selection of these sensors is influenced by the robot's locomotion method and the operational environment. To enhance perception, sensor fusion techniques are used to combine data from multiple sensors, providing a unified understanding of the robot's state and surroundings [1]. However, the occurrence of faults in any robot within the system can jeopardize the successful completion of the assigned task. For example, in a team of mobile manipulator robots handling objects, a single robot malfunction could lead to mission failure [2]. Faults may arise in actuators, sensors, or other components, underscoring the need for reliable actuator and sensor systems to ensure seamless operation. To address these challenges, fault-tolerant cooperative control (FTCC) has been developed as an approach to design adaptive controllers that sustain system performance within acceptable limits, even when faults occur. Various FTCC methodologies and emerging trends have been explored by [3].

A fault-tolerant control system may automatically maintain stability and give adequate performance even when component failures occur. Kheirandish *et al.* [4] reveal a fault-tolerant sensor fusion method for mobile robot localization, using input from two IMU sensors and a wheel encoder to predict the robot's position, together with a multi-model Kalman filter for fault detection. Similarly, Chang *et al.* [5] present an adaptive distributed fault-tolerant formation control (FTFC) for multi-robot systems dealing with actuator faults. Another approach, reported in [6], leverages a nonlinear model predictive controller (NMPC) to exploit the actuation redundancy of omnidirectional robots, giving a real-time unified solution for handling different actuation fault scenarios. Effective fault detection and isolation (FDI) are critical for decision-making in fault-tolerant systems. Abid and Khan [7] introduced an FDI approach based on multi-sensor fusion and validated it in simulated robot navigation under various infrared (IR) and camera fault situations. Also, Abid *et al.* [8] present an FDI technique using multi-level data fusion and behavioral analysis, integrating pre-processing, sensor fusion, conflict monitoring, confidence level computation, and fault isolation. For hardware defect detection, Zweigle *et al.* [9] developed a customizable framework for context awareness in mobile robots, primarily addressing hardware fault diagnostics. Additionally, Crestani *et al.* [10] add fault tolerance into real-time robot control topologies, employing specific software components for fault detection and integrating residual-based diagnosis with signature analysis to identify problematic hardware or software. Finally, Doran *et al.* [11] offer an autonomic fault-handling architecture for mobile robots, proven through case studies involving wheel, sonar, and battery failures. For the overall multi-robot system to complete the assigned tasks, the system needs to be fault-free or capable of adapting to faults that may occur in any of the individual agents. Additional studies, such as [12] and [13] present FTFC approaches for multi-robot systems in the presence of actuator faults.

Regarding the context of formation control, various techniques have been developed for multi-robot formation control. Oh *et al.* [14] provide a comprehensive review of formation control strategies. Also, Recker *et al.* [15] conducted a comparative study of various approaches to formation control for nonholonomic mobile robots in the context of object transportation. The study specifically focuses on comparing the leader-follower formation control approaches, including the ψ-controller and the Cartesian reference-based controller. The study conducted by Roy *et al.* [16] proposed a hierarchical control strategy that enables robots to maintain strong inter-agent cohesiveness while adapting their formation in response to dynamic environmental changes. This approach ensures that the system can effectively navigate toward the target. In addition to formation control strategies, Wu *et al.* [17] proposed a distributed formation control law based on the complex Laplacian matrix. This approach enables a group of mobile robots to achieve the desired formation at a specified speed while ensuring the consistent realization of similar formations in multi-robot systems by utilizing the relative positions of two designated leaders. LiDAR-based localization for formation control in multi-robot systems was proposed by Recker *et al.* [18]. This approach computes the relative positions and velocities of robots directly from LiDAR data. Additionally, the authors developed an algorithm that utilizes LiDAR data to detect the outlines of individual robots. A formation control approach based on machine learning was presented by Rawat and Karlapalem [19]. This study introduced a multi-agent reinforcement learning model to design a control policy that enables robots to maintain a required formation while moving toward a desired goal. Furthermore, Jiang *et al.* [20] present a comparative analysis of model-based and learning-based approaches for formation control. The findings indicate that model-based methods are efficient and reliable when accurate system models are available and uncertainties are moderate. In contrast, learning-based methods demonstrate greater adaptability and robustness in complex and uncertain environments. Additionally, different researchers investigated various approaches in multi-robot formation control [21], [22], and [23].

In multi-robot systems, individual robots may experience subsystem failures, such as actuator or sensor malfunctions. When such a failure occurs, the affected robot is typically isolated from the system, reducing the total number of operational robots. However, certain tasks require the system to maintain a minimum number of active robots to ensure successful task completion. Consequently, the failure of a single robot can lead to systemic failure, preventing the entire system from executing its assigned task. Existing studies have not adequately addressed this issue, leaving a critical research gap. To bridge this gap, this paper proposes a robot replacement strategy within a decentralized fault-tolerant control framework for multi-robot systems. The proposed approach involves replacing the faulty robot with a reserved standby unit while isolating the malfunctioning robot. Furthermore, a graph-theoretical method is employed to ensure stable and precise formation control. The robots in this system utilize an inertial measurement unit (IMU), wheel encoders, and LiDAR sensors for localization and navigation. This study specifically focuses on mitigating LiDAR sensor failures. Due to budget constraints, the proposed method is implemented and validated in a simulation environment (MATLAB/Simulink).

2. METHOD
2.1. Four-wheel differential mobile robot
The present study investigates a multi-robot system (MRS) comprising five mobile robots. The system utilizes four-wheel differential drive mobile robots to explore Spare-assisted fault-tolerant formation control (SA-FTFC). A schematic diagram of the robot is illustrated in Figure 1, where L represents the robot wheelbase. V_R and V_L denote the linear velocities of the right and left wheels respectively, while ω and v are the robot's angular and linear velocities respectively. The position of the robot is defined by the coordinates. (x, y), and ψ represent the robot orientation. The robot's position and orientation represent the robot's state in the global frame. The general coordinate vector is defined as q(t) = $[x(t), y(t), \theta(t)]^T$ and the control input vector is u(t) = $[v(t), \omega(t)]^T$. The kinematic model of a differentia wheel drive illustrated in Figure 1 is described by Kumar [24].

The mobile robot is equipped with a quadratic wheel encoder to determine the wheel direction. The encoder resolution is 1,600 pulses per revolution. The robot wheelbase is 21 cm, and the wheel encoder measurement model is illustrated in the equation.

$$V_R = \frac{2\,\pi\,\Delta\text{ticks}_R}{\text{resolution}*\text{dt}} \;,\; V_L = \frac{2\,\pi\,\Delta\text{ticks}_L}{\text{resolution}*\text{dt}} \tag{1}$$

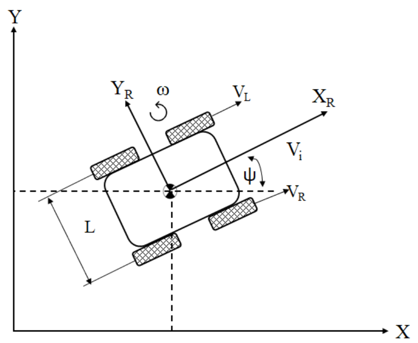


Figure 1. Four-wheel differential drive mobile robot model

2.2. Graph theory
Graph theory is employed to model the communication topology and the formation structure of the multi-robot system (MRS). An undirected graph $\mathcal{G}$ is defined as a pair $(\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of vertices, denoted as $\mathcal{V} = [v_1, v_2, \dots, v_n]$ and n corresponds to the number of nodes, which signifies the total number of robots in the MRS. Additionally, $\mathcal{E}$ represents the set of undirected edges, where $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. The edges connect pairs of vertices such that if the vertex pair $(i, j) \in \mathcal{E}$, then is $(j, i) \in \mathcal{E}$. The number of edges l satisfies $l \in \left\{1, \dots, \frac{n(n-1)}{2}\right\}$. The set of neighbours of vertex i is represented by $\mathcal{N}_i(\mathcal{E}) = \{j \in \mathcal{V} \mid (i,j) \in \mathcal{E}\}$. Further illustration on graph rigidity theory can be found in Zelazo and Zhao [25].

2.3. Fault detection
Every mobile robot in this work is fitted with a LiDAR sensor, wheel encoders, and an IMU to enable mapping and localization. The main goal of the study is to fix LiDAR sensor-related problems. The literature has described a range of defect detection and isolation (FDI) methods [26]. The fault detection method used in this paper computes residuals using two independent techniques: i) by comparing the robot's state estimation obtained from its LiDAR sensor with that of a corresponding LiDAR sensor mounted on another robot within the MRS) and ii) by comparing the LiDAR-based state estimation with the fused state estimation derived from heterogeneous onboard sensors, namely the wheel encoders and IMU. An extended Kalman Filter (EKF) combines wheel encoders and IMU data to accomplish sensor fusion. If the residuals computed using both methods exceed a predefined threshold, this serves as an indication that the LiDAR sensor has encountered a fault.

3. ROBOT REPLACEMENT APPROACH
In multi-robot systems (MRS), robots are programmed to form unique geometric arrangements customized to the requirements of diverse jobs, including material handling, search operations, and

agricultural applications. Certain tasks involve exact spatial formations to ensure optimal performance. However, the occurrence of faults in individual robots poses a considerable difficulty, as it might lead to the isolation of the affected robot and, subsequently, upset the overall system design. To address this issue, the present study provides a Robot Replacement approach aimed at preserving system functionality and formation integrity in the event of robot defects. The proposed solution involves replacing malfunctioning robots within the MRS to preserve the desired configuration. The system under discussion comprises of five robots, where three robots actively maintain a triangular arrangement, and two function as redundancy units capable of swapping faulty ones. The sets of active robots, redundant robots, and the designated leader are labelled as follows: A= 1,2,3}, R={4,5}, and L=1, respectively. Here, A represents the set of actively forming robots, R signifies the set of spare robots, and L indicates the leader robot, defined as the robot with the least identification (ID) number inside the active set. In the presented work, the active robots maintain a triangle formation utilizing a leader-follower control approach. The leader, defined by the lowest ID among the active robots, guides the formation. For instance, if the active robots are R1, R2, and R3, then R1 is assigned as the leader, as specified in (2). The follower robots dynamically modify their locations to preserve the required relative configuration with regard to the leader, as illustrated in the rigidity graph shown in Figure 2.

$$L = \arg\min_{R_i \in A} id(R_i) \tag{2}$$

The fault handling technique adopted in this study contains two basic stages: fault detection and robot replacement. The fault identification technique explicitly targets LiDAR sensor defects. In the robot replacement phase, if a robot n∈M encounters a fault, it is removed from the active set A and replaced by a reserved robot j∈R, where j is picked as the reserved robot with the least identification number. This guarantees a seamless transition and continuation in the formation by updating the active set A accordingly.

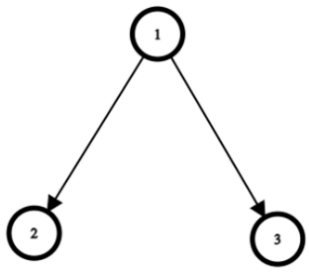


Figure 2. Graph rigidity for triangle shape formation

4. SIMULATION AND RESULTS

The control algorithms outlined in section 3 are implemented and assessed in a multi-robot simulation environment using MATLAB/Simulink. The configuration consists of five differential-drive mobile robots, with three (R_1, R_2, and R_3) functioning as active robots and the other two (R_4 and R_5) working as reserves. The simulation analyses two different scenarios:

a. Fault-free operation: The active robots retain a triangle shape while collectively navigating toward a preset target.
b. Single robot fault: When robot 2 fails, it is replaced by robot 4, following which the formation begins its journey toward the goal.

4.1. Fault-free operation scenario

In this scenario (as in Figure 3), the robots' initial positions are defined according to Table 1 and illustrated in Figure 3(a). Each robot is issued a unique ID (1–5), with the leader position given to the robot with the smallest ID. The initial formation comprises R_1, R_2, and R_3, organized in a triangle formation as depicted in Figure 3(b). The goal positions for R_2 and R_3 are computed relative to R_1 using the Hungarian method to optimize cost efficiency. Robots R_4 and R_5 function as reserved robots, by remaining inactive unless activated to replace a faulty robot.

The results of this scenario are presented in Figure 4. As depicted in the figure, the robots successfully converge to the triangular formation at t=34.5 s. Figures 4(a) and 4(b) illustrate the distance error relative to the leader and relative to the goal position, respectively. While Figure 4(c) illustrates the angle error relative to the leader. Specifically, R2 exhibits a distance error of 0.059 m and an angle error of 1.2º relative to the leader R1, while R3 demonstrates a distance error of 0.061 m and an angle error of 1.22º relative to R1.

Table 1. Robot positions in fault-free operation

Robot ID	Robot status	Starting positions			Goal position		Fault status
		x	y	ψ	x	y	
R_1	Active	25	25	π/2	25	25	False
R_2		15	25	π/2	21.47	14.14	False
R_3		10	35	π/2	19.29	20.85	False
R_4	Reserved	30	40	π/2	30.70	20.85	False
R_5		35	25	π/2	28.52	14.14	False

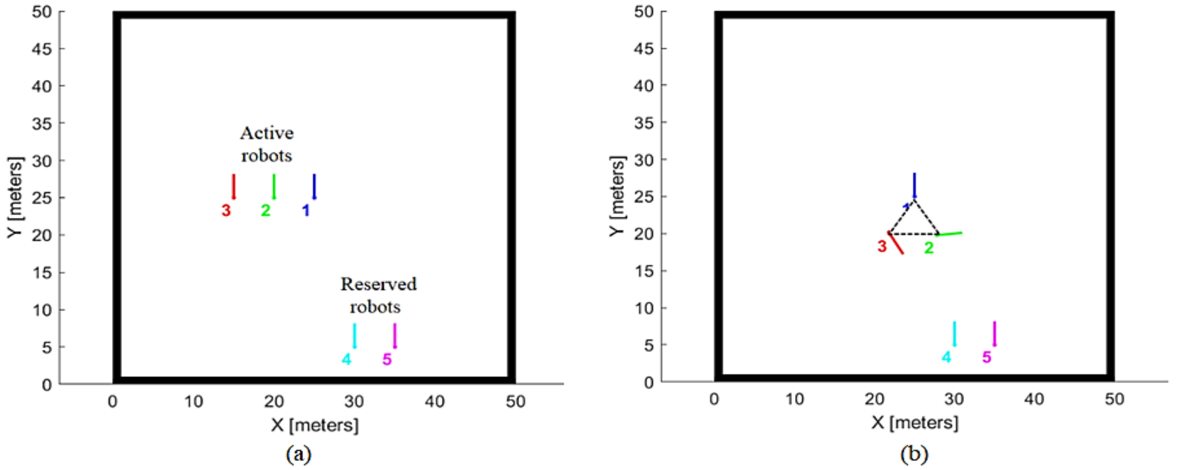


Figure 3. Fault free operation scenario (a) robots start position and (b) robot forming triangle shape formation

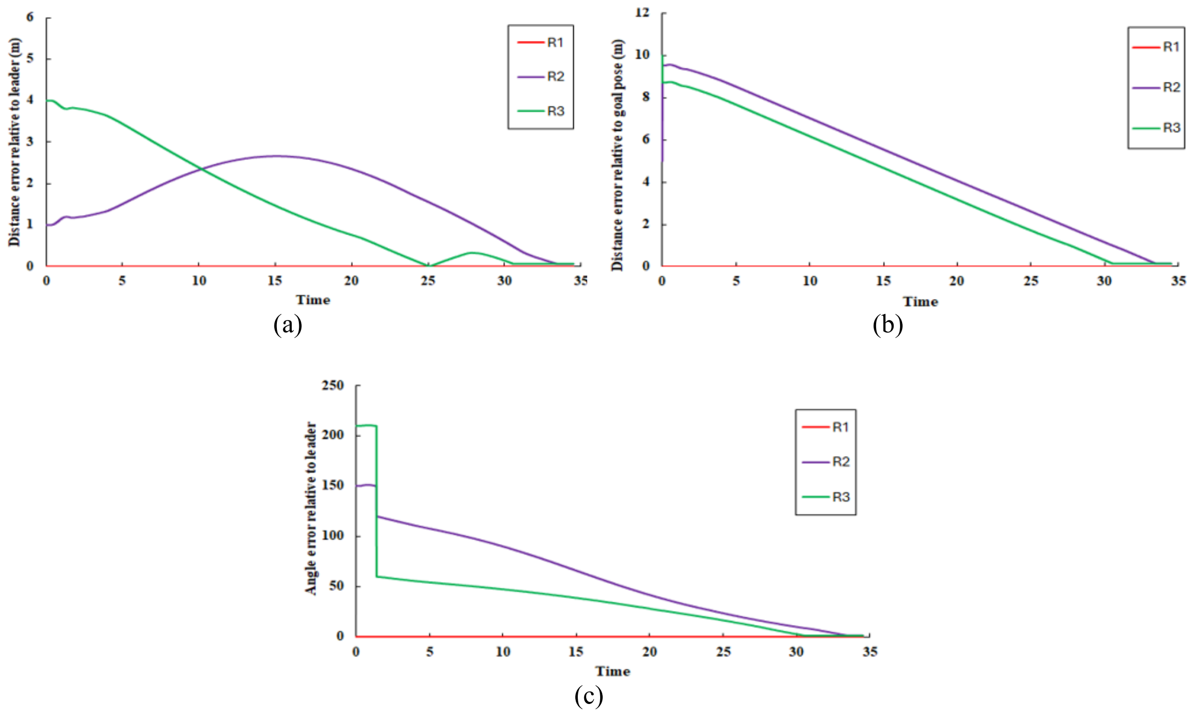


Figure 4. Triangle shape formation errors: (a) distance error relative to the leader, (b) distance error relative to goal position, and (c) angle error relative to the leader

4.2. Single robot fault

In this simulation scenario, robot 2 encounters a LiDAR sensor fault. As noted in [26], LiDAR sensors are prone to various malfunctions. The specific fault examined in this study affects the LiDAR's motor, halting its rotation. As a result, the LiDAR scan is confined to a fixed angle, severely limiting its field of view. Additionally, proper operation of LiDAR sensor systems sometimes requires calibration between the LiDAR and its motor. To address such faults, this study employs the robot replacement method, which replaces the faulty robot with a functional one. When Robot 2 fails, it is removed from the active robot set, initially defined as A = {1, 2, 3}, and moved to a predetermined location on the map. A reserved robot, robot 4 selected from the reserved robot set R = {4, 5} then takes its place. This updates the active set to A = {1, 3, 4} and the reserved robots set to S = {5}. The replacement process is illustrated in Figure 5.

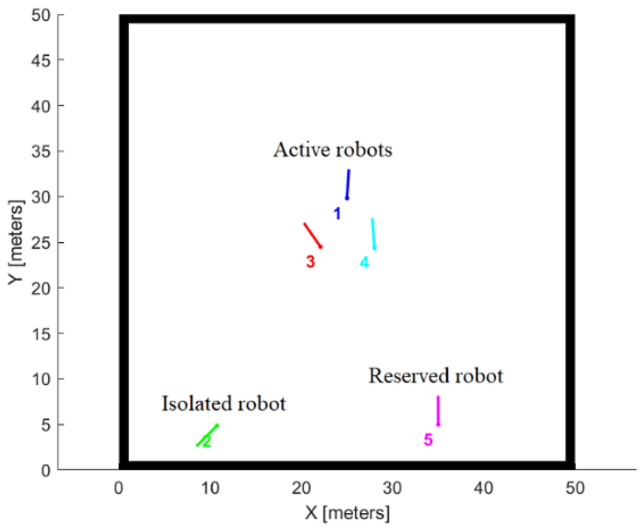
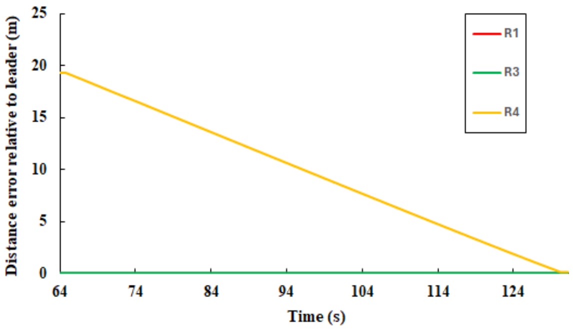
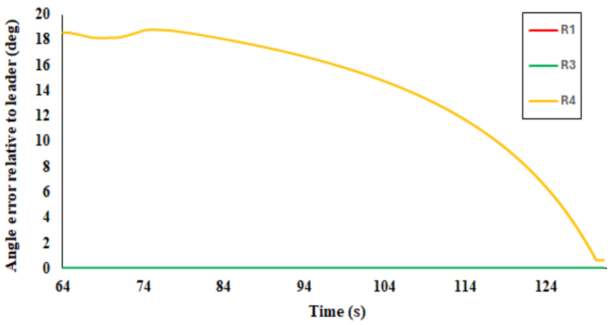


Figure 5. Robto2 isolation and replacement

As illustrated in Figure 5, robot 4 successfully converges to the posture (27.8, 24.6), joining robots 1 and 2. This establishes the active robot set A = {1, 3, 4} in a triangle shape. Meanwhile, the malfunctioning robot 2 is separated from the MRS and goes to its designated isolation point at (10, 5). Figure 6 exhibits errors in robot formation in case a robot encounters a fault, the distance and angle errors of robot 4 relative to the leader R1 are illustrated in Figure 6(a) and Figure 6(b) respectively. The results reveal that robot 4 successfully stabilizes in formation, attaining a final distance error of 0.15 m and an angle error of 0.65°.





(a) (b)

Figure 6. Single robot fault: (a) distance error relative to the leader robot 1 and (b) orientation error relative to the leader robot 1

5. DISCUSSION

The simulation results presented in this study demonstrate the effectiveness of the proposed robot replacement strategy in maintaining formation integrity and mission continuity in MRS experiencing sensor faults. In both fault-free and fault scenarios, the system successfully preserved the triangular formation, indicating the robustness of the robot replacement approach. The smooth transition from a faulty robot to a reserve unit, coupled with rapid convergence to desired spatial configurations, emphasizes the practicality of integrating redundancy in formation-critical tasks. However, while the simulation provides encouraging evidence, real-world implementations may encounter additional challenges, such as communication latency, unstructured environments, and unforeseen sensor noise or hardware limitations. Moreover; future work must consider concurrent multi-robot faults. Enhancements in real-time fault diagnosis, including adaptive thresholds or machine learning-based anomaly detection, could further improve system resilience. Ultimately, extending the framework to physical robot platforms will be essential to validate the simulation results under realistic conditions and assess the feasibility of deploying such systems in industrial, agricultural, or search-and-rescue operations.

6. CONCLUSION

This paper introduces a robot replacement approach to improve fault tolerance in MRS, where maintaining formation size is crucial. The framework was tested in simulations employing five differential wheeled mobile robots: three forming a triangle leader-follower configuration and two serving as spares. Upon failure, an active robot was transferred to a specified isolation position and replaced by the lowest-ID available spare robot, guaranteeing formation stability and system resilience. The proposed technology has considerable potential for industrial automation, including material handling, logistics, and search-and-rescue operations. Future work pending additional funding will focus on real-world MRS implementation and strengthening fault identification, such as real-time LiDAR intensity monitoring for enhanced diagnostics.

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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.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ahmed M. Elsayed	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Mohamed Elshalakani	✓			✓			✓			✓				
Sherif Ali Hammad						✓				✓		✓		
Shady Ahmed Maged		✓					✓		✓			✓		

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

The authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available in the article.

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