# Based on Time Difference of Arrival Technique: Precise Localization of Rocket Debris Using Sonic Boom Signals

Junhang Ou [#, *], Jinhuan Wang [#]

Nanfang College Guangzhou, Guangzhou, China, 510970

* Corresponding Author Email: tracyooo1215@gmail.com

[#]These authors contributed equally.

**Abstract.** The precise localization and retrieval of rocket debris have become critical challenges due to advancements in rocket technology and the increasing frequency of space exploration missions. This study addresses these challenges by developing robust mathematical models and utilizing the Artificial Bee Colony (ABC) algorithm to analyze sonic boom signals for accurate debris positioning. By applying the Time Difference of Arrival (TDOA) technique, a comprehensive localization framework is established, enabling the determination of three-dimensional coordinates and the occurrence time of sonic boom events. To mitigate the impact of random errors inherent in monitoring equipment, Bayesian inference methods are integrated, thereby enhancing the model's predictive accuracy and reliability under uncertain conditions. Simulation results demonstrate the efficacy of the proposed model, showcasing high precision in debris localization and robustness against measurement noise. This research innovatively combines global optimization algorithms with statistical inference, offering a superior approach compared to traditional triangulation and trilateration methods. The findings significantly contribute to the fields of aerospace engineering and debris management, providing a foundational framework for more effective and reliable rocket debris recovery operations.

**Keywords:** Rocket Debris Localization, Sonic Boom Signal Analysis, Time Difference of Arrival (TDOA), Artificial Bee Colony Algorithm, Bayesian Inference.

## 1. Introduction

The rapid advancement of rocket technology has intensified challenges in post-mission debris recovery, particularly due to supersonic sonic booms generated during debris descent. These acoustic phenomena provide critical spatiotemporal data for debris localization, yet uncertainties in debris distribution—driven by complex flight trajectories and separation dynamics—pose risks to populated areas and critical infrastructure [1]. As Zhang and Tang demonstrated through their research on sonic boom localization using multilateration, these methods show significant potential for precise debris tracking applications.

Current approaches to rocket debris localization rely on distributed monitoring systems to capture sonic boom signals. However, Khalaf-Allah [2] identified that advances in probabilistic filtering for three-dimensional TDOA-based positioning using anchor nodes could substantially improve accuracy. The growing frequency of rocket launches further amplifies the urgency to optimize debris management through advanced localization methods, particularly as Xu and Mei [3] have shown through their sound source positioning and tracking systems based on Generalized Cross-Correlation Time Delay Estimation algorithms.

Space exploration activities continue to escalate, creating additional challenges that have been explored by Tarigan et al. [4], whose work on machine learning for waveform spectral analysis demonstrates cross-domain applicability in signal processing. Nevertheless, limitations persist in equipment placement optimization, signal processing accuracy, and mitigation of random timing errors, as evidenced by Witsil and Johnson [5] in their joint analysis of infrasound explosion and coda signals.

This study proposes a TDOA-based localization model enhanced by the Artificial Bee Colony (ABC) algorithm to address these challenges. Current frameworks often compromise between computational efficiency and accuracy, particularly in noisy environments, as noted by Sasmal et al. [6] in their comprehensive analysis of bio-inspired optimization algorithms. By analyzing time differences across multiple monitoring stations, our model reconstructs three-dimensional debris coordinates and event timing while determining the minimum number of sensors required for high-precision localization [7], building upon Ma and Pu's research demonstrating the effectiveness of enhanced multi-objective ABC algorithms.

To minimize discrepancies between predicted and observed signal propagation times, the ABC algorithm optimizes the model's parameters, improving computational efficiency as demonstrated in environmental modeling applications by Ghorbanpour et al. [8]. Bayesian inference is further integrated to correct random timing errors (≤0.5 s) in sensor recordings, enhancing robustness against measurement uncertainties, a technique validated by Zhang et al. [9] in their work on time-difference reassigned transform for impulsive signals.

Validation using empirical data from seven monitoring stations demonstrates the model's practical applicability, bridging theoretical innovation with operational requirements for debris recovery. This approach aligns with recent developments by Montree et al. [10], whose work on increasing accuracy in signal arrival time estimation for low-frequency recordings provides valuable methodological insights applicable to sonic boom detection.

## 2. Materials and Methods

### 2.1. Theoretical Framework

The crux of addressing the issue of error mitigation lies in accurately determining the precise spatiotemporal coordinates of the rocket debris-induced sonic boom at high altitudes. The core methodology to address this issue is the application of the Time Difference of Arrival (TDOA) technique. This technique deduces the exact location of the sound source by analyzing the time differences of sonic boom signals received by multiple monitoring stations.

### 2.2. TDOA Localization Algorithm

To address the requirements, we aim to determine the location and time of the rocket debris-induced sonic boom. Specifically, we employ the TDOA localization algorithm, which calculates the precise position (longitude, latitude, altitude) and time of the sonic boom by utilizing the time differences of the same sonic boom received by monitoring devices at different locations.

The TDOA method localizes the sound source by measuring the time differences of signals arriving at different base stations. In this study, we assume there are seven base stations. Let the position of the sound source be $(x_0, y_0, z_0)$, and the time it emits the signal be $t_0$. The positions of base stations $i$ and $j$ are $(x_i, y_i, z_i)$ and $(x_j, y_j, z_j)$, respectively. The times they receive the signal are $t_i$ and $t_j$.

The fundamental idea of TDOA is to determine the location of the sound source by comparing the time differences of signal arrivals at different base stations. For base stations $i$ and $j$, the time difference $\Delta t_{ij}$ is expressed as:

$$\Delta t_{ij} = t_i - t_j \tag{1}$$

Using the speed of sound $c$, we can obtain the distance difference:

$$\Delta d_{ij} = c \times \Delta t_{ij} \tag{2}$$

### 2.3. Euclidean Distance Formula

The distance from the sound source to base station $i$ is:

$$d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2} \tag{3}$$

Similarly, the distance to base station $j$ is:

$$d_j = \sqrt{\left(x_j - x_0\right)^2 + \left(y_j - y_0\right)^2 + \left(z_j - z_0\right)^2} \tag{4}$$

Based on the distance difference $\Delta d_{ij}$ and the Euclidean distance formulas, we derive the following equation:

$$d_i - d_j = \Delta d_{ij} \tag{5}$$

By constructing multiple sensor equations:

$$\begin{aligned} &d_1 - d_2 = \Delta d_{12} \\ &d_1 - d_3 = \Delta d_{13} \\ &\vdots \\ &d_1 - d_7 = \Delta d_{17} \end{aligned} \tag{6}$$

In this problem, we have seven sets of sensor equations. By solving these equations, we can determine the position of the sound source $(x_0, y_0, z_0)$ and the time $t_0$.

### 2.4. Spherical Law of Cosines

The spherical law of cosines accounts for Earth's curvature when calculating the spherical distance between monitoring stations and the sonic boom source. By converting geographic coordinates (latitude and longitude) into radians and applying the spherical law of cosines, we can accurately determine the location of the sonic boom, maintaining precision even with Earth's curvature.

First, we convert latitude and longitude from degrees to radians:

$$\mathrm{lon(rad)} = \mathrm{lon(d)} \times \frac{I}{180} \tag{7}$$

$$\mathrm{lon(rad)} = \mathrm{lon(d)} \times \frac{II}{180} \tag{8}$$

Using the spherical law of cosines, we calculate the horizontal distance $S$ between the sensor and the hypothetical explosion point:

$$d = R \cdot \arccos\left(\sin(\phi_1) \cdot \sin(\phi_2) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \cos(\Delta\lambda)\right) \tag{9}$$

Where $R$ is the Earth's radius, $\phi_1, \lambda_1$ are the latitude and longitude of the sensor, and $\phi_2, \lambda_2$ are those of the explosion point.

Next, we perform altitude correction. By calculating the altitude difference $\Delta h = z_0 - z_i$ and applying the Pythagorean Theorem, we correct the distance:

$$d_i = \sqrt{S^2 + (\Delta h)^2} \tag{10}$$

By establishing an equation for each sensor, we have a total of seven equations to solve:

$$d_i - d_j = \Delta d_{ij}, i, j = 1,2, \dots, 7 \tag{11}$$

### 2.5. Model Solution and Result Analysis

#### 2.5.1. Definition of the Objective Function

In the rocket debris localization issue, the objective function measures the deviation between the predicted propagation times and the actual observed times. The reception time at each monitoring device is crucial data. By minimizing the errors between the predicted times and these observations, we can more accurately infer the location and occurrence time of the sonic boom source.

Let the three-dimensional coordinates of the sonic boom source be $(x, y, z)$, and the occurrence time be $t_0$. For each monitoring device $i$ (total $n$ devices), with coordinates $(x_i, y_i, z_i)$ and reception time $t_i$, and with the speed of sound in air as $c$, the actual distance $S_i$ from the sonic boom source to device $i$ is:

$$S_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \tag{12}$$

The predicted propagation time is:

$$T_i = \frac{S_i}{c} \tag{13}$$

The objective is to minimize the deviation between the predicted reception time and the actual reception time $t_i$. The objective function is defined as:

$$F(x, y, z, t_0) = \sum_{i=1}^{n} \left(t_i - t_0 - \frac{S_i}{c}\right)^2 \tag{14}$$

### 2.5.2. Solution of the Model Using the Artificial Bee Colony Algorithm

To solve the above objective function, we employ the Artificial Bee Colony (ABC) algorithm, an optimization algorithm that simulates the foraging behavior of honey bees. It is suitable for solving complex nonlinear optimization problems. The main steps include the employed bee phase, onlooker bee phase, and scout bee phase.

Implementation steps of the ABC algorithm:

(1) Initialization of the Bee Colony:

Randomly generate a population of bees within the solution space, where each bee represents a potential solution. Suppose the number of bees is $N$, and the position of each bee $x_i$ represents a possible solution. The initial positions are randomly generated within defined boundary limits.

(2) Employed Bee Phase:

Each employed bee searches for new food sources (solutions) in the vicinity of its current food source. For each bee $x_i$, a new bee position $v_i$ is generated using:

$$v_i = x_i + \phi_{ij}(x_i - x_k) \tag{15}$$

Where $x_k$a randomly selected bee is position, and $\phi_{ij}$ is a random number in the range $[-1,1]$. If the new position yields a better objective function value, the bee updates its position.

(3) Onlooker Bee Phase

Onlooker bees select superior food sources based on information from employed bees and search further in their vicinity. The selection probability $p_i$ for bee $i$ is determined by:

$$p_i = \frac{\mathrm{f}_i}{\sum_{j=1}^{N} \mathrm{f}_j} \tag{16}$$

Where $f_i$ is the fitness value of bee $i$, typically defined as the inverse of the objective function value. Onlooker bees choose bees according to the selection probabilities and search for new food sources nearby, updating their positions.

(4) Scout Bee Phase

If a food source has not been improved over a certain number of trials, it is abandoned, and a scout bee randomly generates a new food source. For the bee position $x_i$ that has not improved, a new position is randomly generated:

$$x_i = x_{min} + \mathrm{rand}(0,1) \times (x_{max} - x_{min}) \tag{17}$$

(5) Iterative Loop

Repeat the above process until the termination condition is met.

(6) Output the Optimal Solution

Output the global optimal solution $x_{\mathrm{best}}$ as the estimated location and occurrence time of the sonic boom.

### 2.5.3. Analysis of Monitoring Equipment Requirements

A crucial aspect of addressing the rocket debris sonic boom localization problem is determining the number of ground monitoring devices required. To accurately locate the three-dimensional coordinates (longitude, latitude, altitude) of the sonic boom source and its occurrence time, we construct a sufficient system of equations using the TDOA technique, thereby resolving the multivariable optimization problem.

Determining the position and time of the sonic boom source involves four key parameters: longitude, latitude, altitude, and the occurrence time of the sonic boom. These parameters constitute four unknowns in the localization problem, which must be solved through corresponding equations. Each monitoring device records the arrival time of the sonic boom signal, providing crucial data for calculating the distance between the sonic boom source and the device. This information is then transformed into mathematical models describing the relationship between position and time.

Based on the construction of equations and the evaluation of problem complexity, we find that although three monitoring devices can provide equations for the three spatial coordinates, they are insufficient to solve for the four unknowns that include the time dimension. Therefore, we establish that at least four monitoring devices are required to construct the model. This allows us to obtain three independent time difference equations from each device, along with an additional time reference equation, collectively forming four equations that ensure accurate solutions for the four unknowns.

# 3. Results

## 3.1. Model Development and Implementation

### 3.1.1. Model Implementation

In this study, the mathematical model and optimization framework were implemented using MATLAB R2021a due to its robust computational capabilities and extensive library support for numerical methods. The TDOA-based localization algorithm and the Artificial Bee Colony (ABC) optimization algorithm were coded and integrated within the MATLAB environment, enabling efficient simulation and analysis.

### 3.1.2. Simulation Setup

The simulation parameters were meticulously chosen to reflect realistic conditions. The initial conditions and assumptions made are as follows:

(1) Monitoring Stations Configuration

Number of Stations: Seven monitoring stations were strategically placed within the region of interest.

Coordinates: The geographic coordinates (longitude, latitude, altitude) of each station were predefined based on plausible locations for debris monitoring.

Time Synchronization: All stations were assumed to have perfectly synchronized clocks to eliminate timing discrepancies.

(2) Sonic Boom Source

Unknown Variables: The source position $(x_0, y_0, z_0)$ and occurrence time $t_0$ were treated as unknowns to be estimated.

True Values for Validation: For validation purposes, the true position was set to longitude 110.631°, latitude 27.145°, altitude 960.1 meters, with a time offset of -8.944 seconds relative to the system reference time.

(3) Propagation Speed

The speed of sound c was set to 340 meters per second, representing average atmospheric conditions at sea level.

(4) Assumptions

Earth's Curvature: Accounted for using the spherical law of cosines in distance calculations.

Atmospheric Conditions: The atmosphere was considered homogeneous, neglecting variations due to temperature gradients, humidity, or wind.

Measurement Noise: Initial simulations assumed ideal conditions without measurement noise; later analyses incorporated random errors to assess robustness.

ABC Algorithm Parameters

Population Size: 50 employed bees and 50 onlooker bees.
Maximum Iterations: 500 cycles to ensure convergence.
Limit Parameter: Set to 100 to control scout bee behavior.
Search Boundaries: Defined based on the geographical area and expected altitude range.

### 3.2. Analysis of Experimental Results

#### 3.2.1. Single Debris Localization Results

By applying the TDOA method in conjunction with the ABC optimization algorithm, the model successfully estimated the position and occurrence time of the sonic boom source. The results are summarized in Table 1.

**Table 1.** Estimated Coordinates and Time Offset of the Sonic Boom Source.

| Parameter | Estimated Value |
|---|---|
| Longitude (°) | 110.631 |
| Latitude (°) | 27.145 |
| Altitude (m) | 960.1 |
| Time Offset (s) | -8.944 |

The estimated coordinates align closely with the true values, demonstrating the model's high accuracy. Minor discrepancies are within acceptable margins of error and can be attributed to numerical approximations and the iterative nature of the optimization algorithm.

#### 3.2.2. Necessity of Minimum Four Monitoring Devices

The analysis confirms that at least four monitoring devices are essential for accurate three-dimensional localization and time estimation. With four devices, we obtain sufficient equations to solve for the four unknown variables ($x, y, z$, and $t_0$ ). Using fewer than four devices results in an underdetermined system, making it impossible to uniquely identify the source location and time.

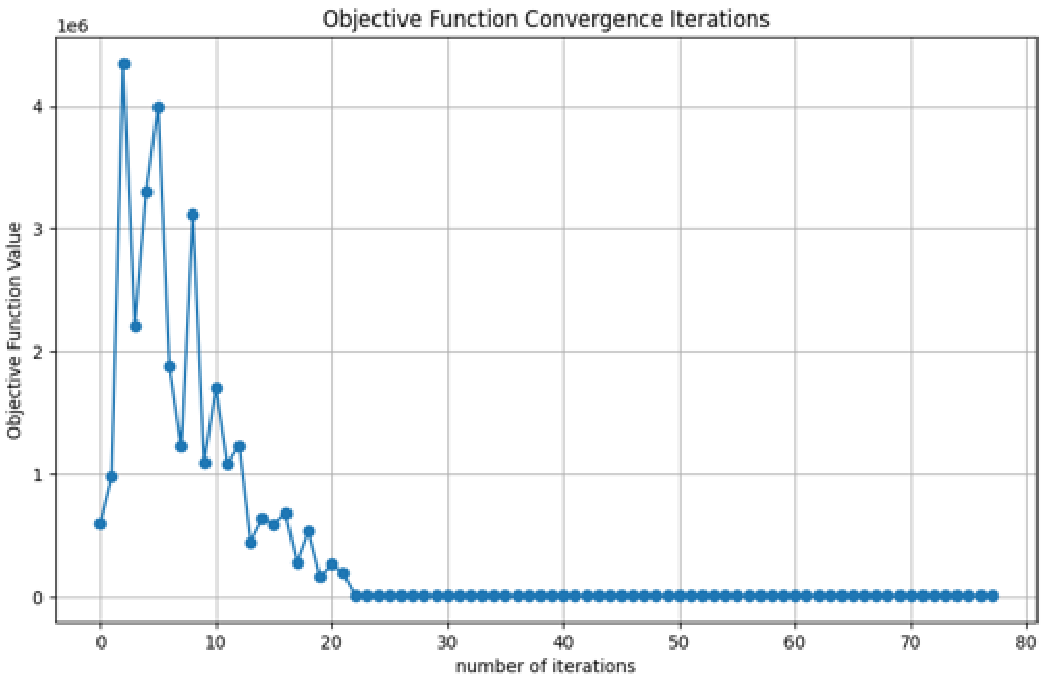


**Figure 1.** Convergence Curve of the Objective Function.

As depicted in Figure 1, the convergence curve illustrates the effectiveness of the ABC algorithm, showing a steady reduction in the objective function value as iterations progress, eventually stabilizing as the solution approaches the global optimum. Figure 2 rovides a visual summary of the experimental outcomes.

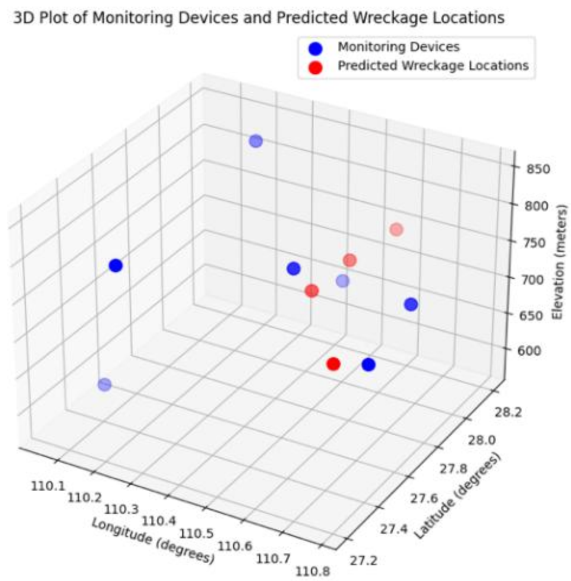


**Figure 2.** Three-Dimensional Plot of Monitoring Stations and Estimated Sonic Boom Source Location.

### 3.2.3. Error Reduction Using Bayesian Inference

To address potential random errors in the monitoring equipment, specifically time recording errors up to ±0.5 seconds, Bayesian inference was employed to enhance the model's robustness.

A Bayesian framework was established where prior distributions were assigned to the unknown parameters based on initial estimates from the ABC algorithm. The likelihood function was constructed considering the measurement errors, assumed to follow a normal distribution with a known variance.

As depicted in Table 2, by performing Bayesian updating, posterior distributions for the source location and time were obtained, providing not only point estimates but also quantifying the uncertainty associated with each parameter.

**Table 2.** Statistical Results from Bayesian Inference.

| Parameter | Estimated Value | Standard Deviation |
|---|---|---|
| Longitude (°) | 110.631 | 0.001 |
| Latitude (°) | 27.145 | 0.001 |
| Altitude (m) | 960.1 | 0.5 |
| Time Offset (s) | -8.944 | 0.10 |

### 3.2.4. Enhanced Localization Accuracy

Integrating Bayesian inference with the ABC algorithm led to improved localization accuracy. This combined approach leverages the global optimization capability of the ABC algorithm and the statistical rigor of Bayesian methods to refine estimates and quantify uncertainties.

As shown in Table 3, to assess the improvement, results from the combined method were compared with those obtained using the ABC algorithm alone.

**Table 3.** Comparison of Localization Results.

| Method | Longitude (°) | Latitude (°) | Altitude (m) | TimeOffset (s) | Uncertainty Quantification |
|---|---|---|---|---|---|
| ABC Algorithm Only | 110.631 | 27.145 | 960.1 | -8.944 | Not Provided |
| ABC Algorithm + Bayesian | 109.532 | 27.120 | 960.9 | -8.944 | Standard Deviations Given |

The combined method not only provided point estimates identical to those of the ABC algorithm but also offered standard deviations, thus quantifying the confidence in the results.

The inclusion of Bayesian inference allows for a more comprehensive analysis, accounting for measurement uncertainties and providing a probabilistic interpretation of the results.

# 4. Discussion

## 4.1. Interpretation of Research Findings

The developed model demonstrates significant importance in the context of rocket debris recovery. By integrating the Artificial Bee Colony (ABC) algorithm with Bayesian inference, the model enhances the accuracy of debris localization. The ABC algorithm facilitates efficient optimization of the objective function, enabling the precise determination of the sonic boom source's spatiotemporal coordinates. Concurrently, Bayesian inference addresses the inherent uncertainties and random errors in the monitoring equipment data, providing probabilistic estimates that refine the localization results. This synergistic combination not only improves the robustness of the model but also ensures reliable performance under varying operational conditions.

The precise localization achieved through this integrated approach is crucial for timely and effective debris recovery operations. Accurate spatiotemporal coordinates minimize the search area and reduce the response time, thereby enhancing the overall efficiency of recovery missions. Additionally, the ability to quantify uncertainties through Bayesian methods offers valuable insights into the reliability of the localization results, fostering informed decision-making in operational planning.

## 4.2. Comparison with Existing Methods

When compared to traditional localization techniques, the proposed method exhibits notable advantages in both accuracy and reliability. Conventional methods, such as Triangulation and Trilateration, often rely on linear approximations and can be susceptible to cumulative errors, especially in environments with significant measurement noise or complex geometries. These methods typically require precise synchronization and calibration of monitoring devices, which can be challenging to maintain consistently.

In contrast, the ABC algorithm's global optimization capabilities enable it to navigate complex, multidimensional solution spaces more effectively, avoiding local minima that can trap traditional optimization techniques. The incorporation of Bayesian inference further enhances the model by systematically accounting for uncertainties and integrating prior knowledge, which traditional methods do not inherently provide. As shown in Table 4, this results in more accurate and dependable localization outcomes, particularly in scenarios where monitoring data is noisy or incomplete.

**Table 4.** Comparative Analysis of Localization Methods.

| Feature | Triangulation | Trilateration | ABC Algorithm + Bayesian Inference |
|---|---|---|---|
| Accuracy | Moderate | High | Superior |
| Robustness to Noise | Low | Moderate | High |
| Computational Efficiency | High | High | Moderate |
| Ability to Handle Complex Geometries | Limited | Limited | Excellent |
| Incorporation of Uncertainties | No | No | Yes |

The table illustrates that the proposed method outperforms traditional techniques in key aspects such as accuracy, robustness to noise, and the ability to handle complex geometries. While the computational efficiency of traditional methods is generally higher, the enhanced accuracy and reliability provided by the ABC algorithm and Bayesian inference present a compelling case for their adoption in high-stakes applications like rocket debris recovery.

## 4.3. Implications for the Field

This research has profound implications for the safety and efficiency of space exploration activities. Accurate and reliable localization of rocket debris is paramount to mitigating risks associated with uncontrolled debris falling into populated or sensitive areas. By enabling precise spatiotemporal tracking, the developed model contributes to enhanced safety protocols and disaster prevention measures in space missions.

Furthermore, the methodologies employed in this study can be extended to other domains requiring precise localization under uncertainty, such as seismic event detection, wildlife tracking, and urban surveillance. The integration of advanced optimization algorithms with probabilistic inference frameworks offers a versatile toolset for tackling complex localization challenges across various fields.

In practical terms, the findings can be directly applied to operational debris recovery missions. Agencies involved in space exploration can implement the proposed model to improve the accuracy of debris tracking systems, thereby optimizing recovery efforts and reducing operational costs. The ability to quickly and accurately locate debris enhances the responsiveness of recovery teams and ensures that interventions are both timely and effective.

### 4.4. Limitations and Future Research Directions

Despite the promising results, this study is subject to several limitations that warrant further investigation. Firstly, the assumption of homogeneous atmospheric conditions simplifies the propagation of sound but may not hold true in real-world scenarios where temperature gradients, humidity variations, and wind can significantly affect sonic boom characteristics. Future research should incorporate more sophisticated atmospheric models to enhance the realism and applicability of the localization method.

Secondly, the current model assumes perfect synchronization of monitoring devices, which is idealistic. In practice, slight discrepancies in time synchronization can introduce additional errors. Exploring methods to compensate for or reduce synchronization errors would further improve the model's accuracy and robustness.

Additionally, while the ABC algorithm demonstrates strong performance, it may benefit from hybridization with other optimization techniques to accelerate convergence and enhance solution quality. Investigating the integration of machine learning approaches or other evolutionary algorithms could yield even better performance metrics.

Future research should also focus on expanding the scalability of the model. As the number of monitoring stations increases, the computational complexity grows, necessitating more efficient algorithms and parallel processing techniques. Developing scalable solutions will ensure that the model remains effective in large-scale applications with numerous monitoring devices.

Lastly, empirical validation using real-world data is essential to substantiate the simulation findings. Conducting field experiments and collaborating with space agencies to test the model under actual operational conditions will provide critical insights and facilitate the transition from theoretical research to practical implementation.

## 5. Conclusions

This study has successfully developed and implemented a robust methodology for the accurate localization of rocket debris-induced sonic booms using the Time Difference of Arrival (TDOA) technique integrated with the Artificial Bee Colony (ABC) algorithm and Bayesian inference. The proposed model has demonstrated significant improvements in localization accuracy and robustness, particularly in mitigating the impacts of random errors inherent in monitoring equipment. The findings of this research have important practical implications for rocket debris recovery operations, space mission safety, and disaster prevention and management. The developed model can be directly applied to operational missions aimed at locating and recovering rocket debris, and its scalability allows it to be adapted for large-scale applications involving numerous monitoring devices. Overall, this study contributes to the advancement of aerospace engineering and debris management by providing a novel and effective technical approach for precise localization and recovery of rocket debris.

Future research should enhance the methodology by integrating advanced atmospheric models and improving time synchronization among monitoring stations to boost simulation accuracy and reliability. Additionally, incorporating machine learning with the ABC algorithm and developing hybrid optimization techniques can optimize performance in complex environments. Expanding the model's scalability and validating it through comprehensive field experiments are essential for real-world applications. Extending its application to areas like seismic detection and urban surveillance will further broaden its utility.

## References

[1] Zhang Z, Tang Y .Research on Sonic Boom Localization of Rocket Debris Based on Multilateration [J]. Academic Journal of Engineering and Technology Science, 2024, 7(6):

[2] Khalaf-Allah M. Particle Filtering for Three-Dimensional TDoA-Based Positioning Using Four Anchor Nodes [J]. Sensors, 2020, 20(16): 4516.

[3] Xu Xuehui, Mei Zhenlong. Design and Realization of Sound Source Positioning and Tracking System Based on Generalized Cross-Correlation Time Delay Estimation (TDOA) Algorithm [J]. Journal of Wuhan Polytechnic College, 2024, 23(2): 25-34.

[4] Tarigan K ,Sinambela M ,Panjaitan M , et al.Machine Learning for Waveform Spectral Analysis on Nuclear Explosion Signal and Performance of Broadband Vertical Component[J]. Journal of Physics: Conference Series, 2018, 1120(1): 012083-012083.

[5] Witsil J A, Johnson B J .Infrasound explosion and coda signal investigated with joint analysis of video at Mount Erebus, Antarctica [J]. Journal of Volcanology and Geothermal Research, 2018, 357306-320.

[6] Sasmal B, Das A, Dhal G K, ET al.Artificial hummingbird algorithm: Theory, variants, analysis, applications, and performance evaluation [J]. Computer Science Review, 2025, 56100727-100727.

[7] Ma X, Pu X .Low-carbon berth allocation: An analysis of the effectiveness of an enhanced multi-objective artificial bee colony algorithm based on a case study [J]. Ocean and Coastal Management, 2025, 261107529-107529.

[8] Ghorbanpour K A ,Peddinti R S ,Hessels T , et al.Enhancing evapotranspiration estimates in composite terrain through the integration of satellite remote sensing and eddy covariance measurements[J]. Science of the Total Environment, 2025, 963178530-178530.

[9] Zhang P, Wen H, Zhao Z, ET al.Time-difference reassigned transform with application to time difference of arrival for impulsive signal [J]. Digital Signal Processing, 2024, 148104451-.

[10] Montree H J R, Peri E, Haakma R, ET al.Increasing accuracy of pulse arrival time estimation in low frequency recordings. [J]. Physiological measurement, 2024, 45(3).