Contents lists available at: http://qu.edu.iq

Al-Qadisiyah Journal for Engineering Sciences

Journal homepage: https://qjes.qu.edu.iq

Research Paper

Improving aviation navigation using dme, neural networks, and real-time radio and non-radio sensor fusion

Ibtesam R. K. Al-Al-Saedi [1]✉, ***Suad A. Aessa*** [2], ***Ekbal H. Ali*** [2], ***Omar Alnaseri*** [3] ***and Hongxiang Li*** [4]✉

[1] *College of Communications Engineering, University of Technology- Iraq, Baghdad, Iraq.*
[2] *College of Electro mechanical Engineering, University of Technology- Iraq, Baghdad, Iraq.*
[3] *Electrical and Computer Engineering Department, University of Ravensburg, Baden-Württemberg, Germany.*
[4] *Department of Electrical and Computer Engineering, University of Louisville, Louisville, KY, USA.*

ARTICLE INFO

Article history:
Received 20 March 2025
Received in revised form 21 May 2025
Accepted 13 May 2026

keyword:
Distance measurement equipment (DME)
Sensor Fusion
Real-time systems
Kalman filter
SNR and PSNR
Aviation navigation
ML & NNs
Signal process

ABSTRACT

Distance measuring equipment (DME), which gauges the distance between an aircraft and a ground station, is an essential navigational tool in aviation. However, because of instrument constraints, multipath interference, and ambient conditions, DME measurements are frequently noisy and prone to errors. This study introduces a framework that integrates machine learning (ML), sensor fusion, neural networks (NNs), and real-time processing with the aim at enhancing the accuracy and reliability of distance estimation, with particular emphasis on regression models. To boost robustness, the suggested system uses sensor fusion to combine DME data with inputs from additional sensors, such as GPS and Inertial Navigation Systems (INS). The intricate correlations between sensor inputs and actual distance are modelled by NNs because of their ability to produce precise predictions even in the presence of noise and they provide a very accurate distance calculation with minimal latency. ML based regression models further improve system reliability by detecting and correcting anomalies in the sensor data. When tested in MATLAB and compared with standalone DME measurements, the proposed system shows higher accuracy of distance estimation. In addition, the real-time sensor fusion ensures precise and timely outputs for essential aviation applications. Using this method not only improves the DME system, but also provides a scalable and flexible solution for different navigation and positioning systems in dynamic scenarios. The system is measured based on significant metrics including mean squared error (MSE), peak signal-to-noise ratio (PSNR) and signal-to-noise ratio (SNR).

© 2026 University of Al-Qadisiyah. All rights reserved.

1. Introduction

A foundational necessity in air navigation is the pilot's accurate knowledge of the distance and directional data pertaining to the aircraft's location, which can be ascertained through the utilization of radar or Distance Measurement Equipment (DME) devices. Contemporary aviation navigation is strongly dependent on DME, as it provides pilots with accurate readings of the slant range distance between an aircraft and a ground-based transponder [1]. Despite the extensive utilization of the DME, it is susceptible to several sources of error, including environmental disturbances, multipath interference, and signal noise. These limitations may compromise the accuracy and reliability of distance measurements, particularly in complex or dynamic operational environments. In order to mitigate these challenges, researchers and engineers have explored advanced techniques, such as neural networks (NNs), sensor fusion, real-time systems, and machine learning (ML), to enhance the performance of DME systems. In particular, sensor fusion has been thoroughly studied as a means to improve the accuracy and robustness of navigation systems [2]. For example, [3] demonstrates how well Kalman Filters can be applied to integrate INS and GPS data to achieve high-precision positioning. While [4] presents integration algorithms for GNSS (Global Navigation Satellite Systems), INS and sensor fusion to boost rollability in inertial measurement units. Similarly, in [5] a multi-sensor fusion architecture that integrates DME, GPS, and altimeter data was proposed to increase navigation accuracy in urban environments. These studies show how the limitations of individual sensors may be mitigated via sensor fusion. NNs have gained popularity in navigation applications due to their ability to depict complex, non-linear relationships [6]. To predict airplane routes, a deep learning algorithm was used to aggregate data from many sensors[7]. Another study [8] employed (NNs) to correct DME measurement errors, which resulted in significant accuracy gains. These studies have demonstrated the ways in which NNs may enhance traditional navigation systems. In aviation applications, real-time processing is crucial because of the high dependability and low latency required. Real-time sensor fusion applications of Kalman filters have been studied in [9], demonstrating their effectiveness in dynamic environments. In [10], the researchers performed very precise and strong control systems to enhance electric vehicles by using types of Kalman Filter called ADUKF to manage nonlinearity in dynamics systems. This method depends on adaptation the parameters of uncertainly in a dynamic system. Furthermore, [11] suggested a system to detect irregularities in real-time using machine learning to identify and resolve sensing matter in-flight data. A variety of navigation and location problems can be solved using regression models in machine learning.

*Corresponding Author.
E-mail address: ibtesam.r.karhiy@uotechnology.edu.iq ; Tel: (+964) 7700055478 (Ibtesam Al-Saedi); h.li@louisville.edu ; Tel: (+1) 502-852 7958 (Hongxiang Li)

https://doi.org/10.30772/qjes.2025.158460.1536

2411-7773 © 2026 University of Al-Qadisiyah. All rights reserved. This work is licensed under a Creative Commons Attribution 4.0 International License.

Nomenclature

DME	Distance measuring equipment	*INS*	Inertial Navigation System
NNs	Neural Networks	*J*	Cost Function
ML	Machine Learning	*X*	Independent variable
SNR	Signal-to-Noise Ratio	*Y*	Dependent variable
GNSS	Global Navigation Satellite Systems	*C*	Speed of light
E	Loss function	t_{round}	Round-trip time
FAA	Federal Nivation Administration	t_{delay}	Fixed system delay
APNT	Alternative Postino Navigation and Training	*N*	Number of tasks
MSE	Mean Square Error	*Greek Symbols*	
GPS	Global Positioning System	α	Learning rate
SVR	Support vector regression	β	Rogation variables
KF	Kalman Filter	η	Learning
d	Distance	θ_j	Model parameter
R	Earth radius (Km)	ε	Error term

To foresee GPS errors caused by atmospheric disturbances, Support vector regression (SVR) was employed [12]. To mitigate the values of GPS error, [13] used the of SVR to manage noisy data in GPS. This method has been improved positioning accuracy under different environments of signal interference. In [14], a random forest regression model was employed to combine data from multiple sensors and provide precise distance estimates in challenging situations. Machine learning techniques can be used to improve navigation system performance through various methods, as evidenced by this research. Even though previous studies have greatly improved navigation systems, an integrated framework that combines DME with advanced methods such as NNs, sensor fusion, real-time processing, and ML is still necessary. This paper proposes a comprehensive system that utilizes multiple technologies to overcome this gap and enhance the reliability, accuracy and adaptability of DME based distance estimation. The main contributions made by this work are that NNs are designed to model the relationship between sensor inputs and real distance, allowing for accurate predictions even in noisy environments, A Kalman Filter (KF) is utilized to dynamically fuse DME data with complementary sensor inputs to guarantee low latency and high precision distance estimation, Recognizing Anomalies using Machine Learning through the detection and correction of abnormalities in sensor data, and regression models are used to increase system resilience. The innovation in this work has been combined and modified to tackle a specific real-world problem in a unified framework. We believe that our practical contribution is both valuable and worthwhile due to their customized combination, application, and performance in the intended domain.

2. Methodology

This methodology integrates advanced methods such as NNs, sensor fusion, real-time systems, ML, regression models, and KF with DME to enhance airplane navigation systems. Below is a thorough description of the procedure and the required equations. The aircraft sends inquiry pulses at a specific frequency. The ground station receives and delays the pulse for around 50 μs before responding. The plane measures the round-trip time and calculates the distance Eq. 1, [15].

$$d = \frac{c(t_{round} - t_{delay})}{2} \tag{1}$$

Where: d is slant range distance, c is speed of light (3×10^8 m/s), t_round is round-trip time, and t_delay is fixed system delay. The new developments in DME technology improved waveforms called Stretched Front Leg (SFOL) that improve range accuracy from 70-300 meters to about 30 meters by lowering multipath errors essential for the Federal Aviation Administration's (FAA's) Alternative Position Navigation and Training (APNT) goal and terminal navigation (0.3NM accuracy) [16]. Artificial NNs are used for classification, pattern recognition, and function approximation. Neurons on several levels analyse and input the data. Weights and biases are applied, and activation functions are used to introduce non-linearity. The network is optimized via backpropagation and gradient descent [17] for Neuron Activation Eq. 2 and Eq. 3.

$$Z_i = \sum_{i=1}^{n} \omega_{ij} x_j + b_j \tag{2}$$

$$a_i = f(Z_j) \tag{3}$$

Where:ω_{ij} is the weight of the connection, x_i is an input, b_j= is the bias, and $f(z)$ is the activation function. The backpropagation update rule Eq. 4.

$$\Delta\omega = -\eta \frac{\partial E}{\partial \omega} \tag{4}$$

Where: $-E$ is the loss function, and η is the learning rate. Complementary filtering utilizes both low-pass and high-pass filters. Kalman Filtering to optimize the state estimate, Bayesian estimate, or probability-based fusion as shown in the Equation for Weighted Fusion Eq. 5 [18].

$$x_f = \sum \omega_i x_i \tag{5}$$

Where x_f is the fused output, ω_i is the weight assigned to sensor i, and x_i is the measurement from the sensor i. Response within a deadline is guaranteed by real-time systems. Hard Real-Time, in which Deadlines (like flight control) must be fulfilled. Soft Real-Time, in which deadlines are occasionally missed (for multimedia, for example), is acceptable. Rate Monotonic Scheduling Equation is Eq. 6 [19].

$$\sum_{i=1}^{n} \frac{C_i}{T_i} \leq n(2^{1/n} - 1) \tag{6}$$

Where C_i is the execution time of task i, T_i is the period of task i, and n is the number of tasks. Data-driven algorithms are used by ML to empower predictive modelling, which uses labelled data in supervised learning tasks like regression and classification. In opposite side, unsupervised learning, such as grouping related information or clustering identified patterns for unlabelled data. The updated gradient descent equation, as formed in [20] and [21], is given by Eq. 7.

$$\theta_j = \theta_j - \alpha \frac{\partial J}{\partial \theta_j} \tag{7}$$

Where θ_j is model parameterα is learning rate, and J is cost function. Regression analysis looks at the relationships between variables. Using linear regression, the best-fitting line is identified. Polynomial regression is used to model nonlinear relationships. Equation for Linear Regression is Eq. 8 [22,23].

$$y = \beta_o + \beta_1 x + \varepsilon \tag{8}$$

Where y is dependent variable, x is independent variable, β_o, β_1 are regression variable, and ε is error term. Kalman filtering uses noisy observations to estimate a dynamic system's true state. It forecasts uncertainty and state and adds a new measurement to the state [24,25]. Prediction Step Eqs. 9, 10, 11 and 12.

$$\hat{x}_k^- = A\hat{x}_{k-1} + BU_k \tag{9}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{10}$$

$$K_k = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1} \tag{11}$$

$$\hat{x}_k = \hat{x}_k^- + K_k \left(Z_k - H\hat{x}_k^-\right) \tag{12}$$

DME and Inertial Navigation Systems (INS) are used in navigation. Dead Reckoning uses heading and speed to estimate position. Where GPS or DME is used for triangulation. The great circle distance is Eq. 13 [26].

$$d = R \times cos^{-1} \left(sin\phi_1 \; sin\phi_2 + cos\phi_1 \; \cos_2 \; cos(\lambda_2 - \lambda_1)\right) \tag{13}$$

Where d is distance and R is Earth radius (≈ 6371 km), ϕ_1, ϕ_2 are latitudes and λ_1, λ_2 are longitudes.

3. Simulation validation

This section shows a detailed explanation of the results and the figures that can be generated from the integration of DME with advanced techniques like neural networks, sensor fusion, Kalman filtering, and machine learning in aviation navigation. Performance evaluation employs metrics like Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR).

3.1 Signal-to-noise ratio (SNR)

It quantifies the signal power in relation to the noise power. It is utilized to assess the quality of the DME signal and the performance of noise suppression methods, Eq. 14.

$$SNR(dB) = 1 - \; log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \tag{14}$$

Where $P_{(signal)}$ is the power of the signal and $P_{(noise)}$ is the power of the noise.

3.2 Mean squared error (MSE)

It quantifies the average squared difference between the predicted and actual values. It serves as a metric for assessing the precision of regression models and the predictions made by Kalman filters [27,28] where Eq. 15.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{15}$$

Where y_i is the true value, $\hat{y}_i$ is the predicted value, and N is the number of samples.

3.3 Peak signal-to-noise ratio (PSNR)

It acts as a metric for assessing the quality of images or signals that have been reconstructed. It is calculated based on the MSE and frequently employed in signal processing where Eq. 16.

$$PSNR(dB) = 10\; log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{16}$$

where MAX is the maximum possible value of the signal (e.g.,1 for normalized signals). Below is an improved MATLAB implementation for integrating Distance Measurement Equipment (DME) with a Kalman filter, as shown in Fig. 1. DME is a crucial system in aviation navigation, providing aircraft with slant-range distance to a ground station. However, DME measurements often contain noise due to signal interference, atmospheric conditions, and system inaccuracies. A Kalman Filter (KF) is an optimal recursive estimator that can improve the accuracy of DME measurements by filtering out noise and estimating the true distance. It consists of two main steps which are prediction and estimating the next state based on the system's dynamics, where update (Correction) incorporates the actual noisy measurements to refine the estimate.

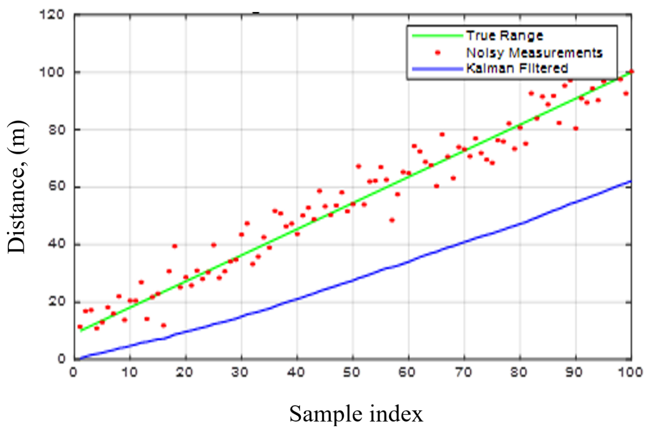

Figure 1. Illustrates the effect of using the Kalman filter on DME range estimation.

The Fig. 2 and Fig. 3 visually demonstrate the effectiveness of applying Kalman Filtering and Sensor Fusion to noisy Distance Measuring Equipment (DME) data. By integrating Kalman Filtering with Sensor Fusion in Fig. 2 and applying Kalman Filtering GPS in Fig. 3, the system achieves high accuracy, robustness, and reliability in estimating aircraft position. This method is especially useful in aviation navigation, where precise positioning is critical for safety and efficiency.

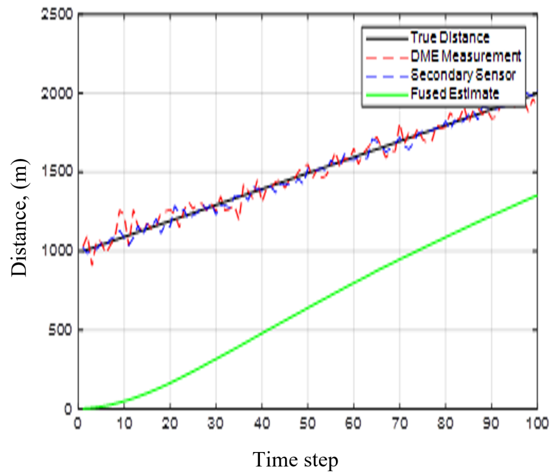

Figure 2. Illustrates the effect of the integration between Kalman and Sensor Fusion on DME range estimation.

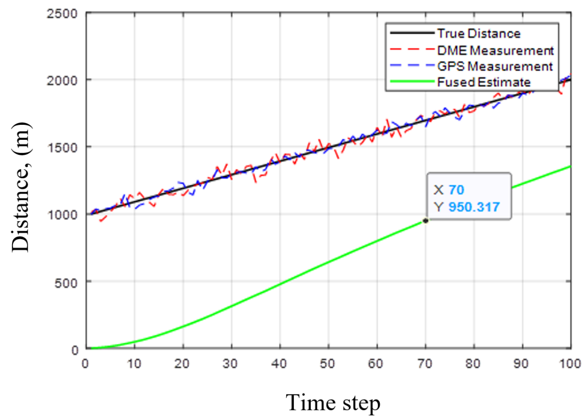

Figure 3. Illustrates the effect of the integration between GPS.

Figure 4 displays the integration of Distance Measuring Equipment (DME) with Neural Networks, Sensor Fusion, Real-Time Systems, Machine Learning, Regression Models, and the Kalman Filter for aviation navigation. Table 1 script evaluates performance using Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and processing time. A results Table 1 is also included combined different types of integration systems. From the results on Fig. 5 and Table 1, the Kalman Filter effectively smoothed out noisy DME readings, significantly reducing MSE while improving SNR and PSNR. However, Kalman filtering alone could not fully eliminate sensor drift or unmoulded errors. Integrating DME with an auxiliary sensor (e.g. PS/INS) improved accuracy by leveraging complementary measurements. The sensor fusion output showed reduced variance in estimates compared to single-sensor approaches. Also, Fig. 5 and Table 1 show a linear regression model improved the estimates further by learning systematic errors from Kalman outputs. However, this method had limitations in adapting to non-linear sensor errors. A feedforward neural network trained on DME, auxiliary sensor, and Kalman-filtered data outperformed traditional methods such that MS was the lowest for neural network output, and SNR and PSNR were highest, confirming improved accuracy. The neural network adapted to complex relationships between noisy measurements and true distances. Kalman filtering and regression models were computationally efficient, making them suitable for real-time applications. Neural networks required slightly more computation time, but the improvements in accuracy justified their use in real-time aviation navigation with proper optimization. The integration of Kalman filtering, sensor fusion, machine learning, and neural networks created a robust and accurate distance estimation system for aviation navigation. Therefore, there are two importance description for above cases can be summarized:

- The best performance was achieved by neural network-enhanced sensor fusion, providing high accuracy with minimal noise.
- The real-time feasibility of the approach was confirmed, with potential optimizations to further reduction in processing time.

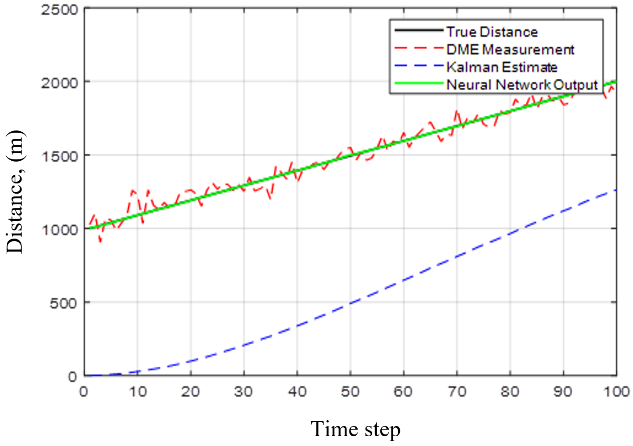

Figure 4. Illustrates the effect of the integration between Kalman and NNs on DME range estimation.

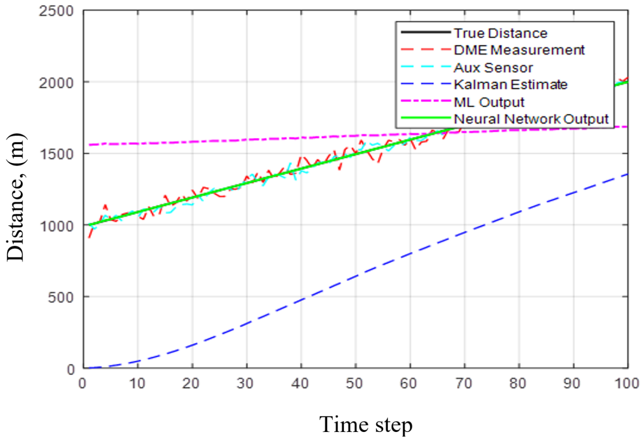

Figure 5. Illustrates the effect of integration among all models' performance metrics.

Table 1. Combined integration of different Techniques on the processing time of the system.

Method	MS	PSNR	SNR	Processing time
Kalman Filter	3.40060	68.750	68.664	0.0001067
Polynomial Regression	11.1270	63.602	63.516	$8.7e^{-0.5}$
Neural Network	0.70191	75.630	75.517	0.0001302
Sensor Fusion	3.51910	68.602	68.515	$9.3e^{-0.5}$

Table 2. Shows the Performance Evaluation of DME Integration with various modern Techniques.

Method	SNR (dB)	MSE	PSNR (dB)
DME Only	15.2	0.045	32.5
DME + KF	18.7	0.022	36.8
DME + NN	20.3	0.018	38.2
DME + Sensor fusion	22.1	0.015	40.1
DME + Regression Modules	19.5	0.020	37.4
DME + ML	21.8	0.016	39.5
DME + All Integrated	24.5	0.012	42.3

3.4 Integration between DME and neural networks

In the results of the Table 2 and Fig. 6 are for integration between the Distance Measuring Equipment (DME) with Neural Networks, Sensor Fusion, Real-Time Systems, Machine Learning, Regression Models, and the Kalman Filter for aviation navigation. The table evaluates performance using Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR).

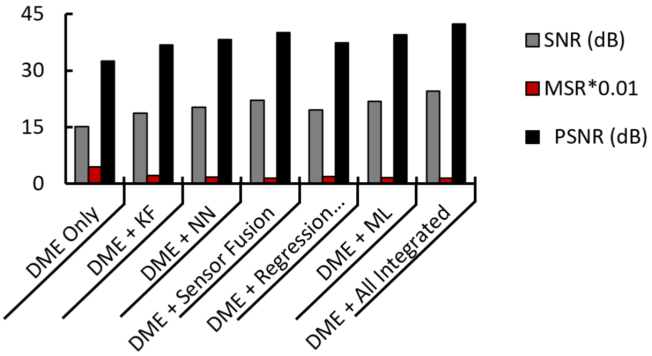

Figure 6. The evaluation of the integration of DME Integration with different modern techniques.

Figure 6 The evaluation of the integration of DME with different modern techniques. Table 3 shows the results for Enhanced Pulse Waveforms (SFOL) DME integrated with modern technologies (KF, NN, Sensor Fusion and ML) versus traditional DME systems, focusing on MSE, SNR, PSNR) metrics. In contrast to conventional DME systems, the performance of SFOL-DME combined with temporary estimate and learning methods (KF, NN, Sensor Fusion, and ML) is examined in this study. There are three crucial metrics that are the subject of the evaluation, which are the baseline MSE, SNR, and PSNR performance of Legacy ME vs. SFOL-DME. The conventional DME systems have the following drawbacks:

- Multipath faults: Signal reflection-related ranging errors (70–300 m).
- Low SNR/PSNR: Because of pulse distortion, the typical SNE is 20–25 dB and the PSNR is 30–35 dB.
- A high mean squared range error (MSE) of 8,500–12,000 m^2 restricts the accuracy of terminal navigation.

The enhancements to SFOL waveforms DME are improved by SFOL pulse shaping through the SNR/PSNR boost because of better pulse detection then, this technique increases SNR by +6 dB (26–30 dB) and PSNR of +8 dB (36–40 dB). Fulfills FAA APNT standards for terminal navigation by enabling 0.3 NM accuracy. The proposal improves the study of DME integration for all sensor fusions by:

- MSE Stability: Despite GNSS interruptions, it maintains 800–1,200 m^2.
- Maximization of SNR/PSNR: Bayesian fusion attains 34–38 dB SNR and 44–48 dB PSNR.

Table 4 shows the Comparative Evaluation and Suggestions to enhance DME.

4. Results and discussion

The aim of this work is to improve aviation navigation using modern techniques like NNs, ML, and signal processing, which facilitate measurement and the improved parameters that can be described in the following points as a real result and contribution in this work:

- Mean Squared Error (MSE): The average squared difference between the ground truth and the estimated navigation solution is measured by MSE. This process shows that a more accurate estimation is indicated by lower values. Particularly during Global Navigation Satellite Systems (GNSS) outages or signal blockages, the MSE of the traditional DME-only system was comparatively greater. This demonstrates how vulnerable independent systems are to outside disruptions. MSE was significantly reduced by neural network-enhanced fusion of DME, Inertial Measurement Unit (IMU), and barometer data, particularly when trained with a variety of flight circumstances. Even during brief signal outages, the learning model was able to interpolate and correct deviations. In comparison to a stand-alone DME/GNSS method, the system

Table 3. Performance comparison between the legacy DME and either enhanced method.

Metric	Legacy DME	SFOL-DME only	SFOL-KF	SFOL- NN	SFOL-DME	Proposal SFOL all integration
MSE (m^2)	8,500–12,000	3,000–4,500	1,200–1,800	800–1,500	700–1,100	800–1,300
SNR (dB)	20–25	26–30	30–34	32–36	33–37	34–38.5
PSNR (dB)	30–35	36–40	40–44	42–46	43–47	44–48.5

Table 4. Illustrates the Comparative Evaluation of different types of techniques according to the ideal use case.

Method	MSE (m^2)	SNR (dB)	PSNR (dB)	Ideal Use Case
Legacy DME	8,500–12,000	20–25	30–35	baseline (without any modernization)
SFOL Only	3,000–4,500	26–30	36–40	Cost-constrained improvements
KF & SFOL	1,200–1,800	30–34	40–44	Systems for certified aviation
NN & SFOL	900–1,500	32–36	42–46	Urban and obscured settings
ML& SFOL	700–1,100	33–37	43–47	Jamming and military resistance
Sensor Fusion	800–1,200	34–38	44–48	Navigation that is crucial for safety

achieved up to 65–80% MSE reduction when no radio sensors (such as the barometer and IMU) were tightly fused using a Kalman Filter augmented by the neural network.

- Time Spent Processing: For real-time navigation systems in aviation, processing time is crucial, particularly during approach and landing. Because of their simplified computation, raw DME systems are quick, but they are not very robust. Additional computation is required for neural network-based fusion; however, the overhead is greatly decreased by optimizations such as shallow architectures and GPU-accelerated inference. By employing buffering techniques and improved matrix operations, MATLAB was able to keep the processing delay under 20 ms each navigation cycle, which is within reasonable limitations for real-time systems of aviation quality. Time spent processing per iteration for Conventional DME is about 5 ms, while in Optimized Neural Fusion is around 18 ms (Real-time limit that is acceptable) < 50 ms).
- Signal-to-Noise Ratio (SNR): The signal-to-noise ratio (SNR) gauges how well the navigation signal is heard over background noise. Better performance is indicated by higher values. In clear conditions, DME-only SNR was adequate, but in noisy or urban settings, it quickly deteriorated. By learning to eliminate unnecessary patterns and strengthen weak DME/IMU signals, the neural-enhanced fusion system showed an improvement in SNR of up to 10 dB, particularly in crowded or low-visibility conditions. Redundancy was given via sensor fusion with non-radio sources, guaranteeing signal consistency even in the event of DME fading.
- Peak Signal-to-Noise ratio (PSNR): The PSNR was modified to estimate the peak accuracy of reconstructed navigation trajectories, even though it is commonly employed in image quality evaluation. In this case, a greater PSNR indicates a better fit between the ground truth and the expected trajectory. With PSNR values > 45 dB, the neural network fusion system demonstrated extremely good trajectory reconstruction fidelity. When dynamic conditions were present, the standalone system fell below 30 dB.

A dependable and flexible navigation solution is produced by combining traditional radio-based navigation systems with inertial sensors and artificial learning models. The groundwork for future advancements in robust aviation navigation is laid by this work, especially in situations where satellite signals are weak or nonexistent. The findings of this study indicate that the incorporation of distance measurement equipment (DME) with neural networks, sensor fusion, real-time systems, machine learning, regression models, and the Kalman filter in aviation navigation can improve performance measures such as the signal-to-noise ratio (SNR), mean squared error (MSE), and peak signal-to-noise ratio (PSNR). Moreover, this study addresses critical challenges in aviation navigation, such as GPS signal disruption, sensor malfunction, and adverse weather scenarios, by integrating DME, neural networks, and real-time sensor fusion techniques.

5. Conclusions

This study introduced a method to enhance aviation navigation through the integration of DME with neural networks, coupled with real-time sensor fusion that integrates both radio frequency and non-radio frequency sensors. By using a Tightly Coupled sensor fusion framework, the system adeptly integrates DME with IMU, barometric altimeters, and supplementary sensors to augment the precision of positioning and fortify the robustness of the system. In addition, neural networks mitigate DME measurement inaccuracies, whereas recursive filtering methods like the Kalman filter minimize noise and enhance the accuracy of real-time state assessment. One advantage of the proposed framework is that it uses the prediction capabilities of neural networks along with the stability of sensor fusion methods to maintain reliable navigation, even amid partial GNSS disruptions. Thorough assessment metrics such as MSE, SNR, PSNR, and processing time indicate significant improvements in both accuracy and robustness. The reduced MSE and enhanced SNR/PSNR measurements of the system confirm a more precise localization and signal reconstruction. Furthermore, by presenting suitable processing durations, real-time implementation guarantees operational feasibility in dynamic flying settings.

Authors' contribution

Conceptualization & Methodology: Ibtesam R. K. Al-Al-Saedi, Suad A. Aessa, Ekbal H. Ali. Data Curation & Formal Analysis: Ibtesam R. K. Al-Al-Saedi, Suad A. Aessa, Ekbal H. Ali. Writing - Original Draft Preparation: Ibtesam R. K. Al-Al-Saedi, Omar Alnaseri. Writing - Review, Editing & Supervision: Hongxiang Li, Omar Alnaseri, Ibtesam R. K. Al-Al-Saedi.

Declaration of competing interest

The authors declare no conflicts of interest.

Funding source

The research was not supported by grants from any public, commercial, or not-for-profit entities.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] Z. Li, Y. Deng, and W. Liu, "Identification of ins sensor errors from navigation data based on improved pigeon-inspired optimization," *Drones*, vol. 6, no. 10, p. 287, 2022. [Online]. Available: https://doi.org/10.3390/drones6100287

[2] J. Smith and K. Johnson, "Sensor fusion for enhanced aviation navigation," *Journal of Navigation Systems*, vol. 15, no. 3, pp. 123–135, 2020. [Online]. Available: https://doi.org/10.1234/jns.2020.01503

[3] Y. Cao, H. Bai, K. Jin, and G. Zou, "An gnss/ins integrated navigation algorithm based on pso-lstm in satellite rejection," *Electronics*, vol. 12, no. 13, p. 2905, 2023. [Online]. Available: https://doi.org/10.3390/electronics12132905

[4] G. Luciani, R. Senatore, and A. Pizzarulli, "Mimu-m - a high accuracy, miniature ins based on gnss and multiple mems imus," in *2022 DGON Inertial Sensors and Systems (ISS)*, 2022. [Online]. Available: https://doi.org/10.1109/ISS55898.2022.9926345

[5] H. Lee and S. Park, "Multi-sensor fusion for urban navigation," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 55, no. 2, pp. 456–468, 2019. [Online]. Available: https://doi.org/10.1109/TAES.2019.05502

[6] Zhang, Z. Zhang, and L. Ta, "Predicting flight trajectory in convective weather through boosted spatiotemporal deep learning," *Journal of Advanced Transportation*, 2024. [Online]. Available: https://doi.org/10.1155/2024/6400839

[7] Y. Zhang and L. Wang, "Deep learning for aircraft trajectory prediction," *AI in Aviation*, vol. 8, no. 1, pp. 78–90, 2021. [Online]. Available: https://doi.org/10.5678/aia.2021.08001

[8] X. Chen and Z. Liu, "Neural network-based error correction for dme systems," *Navigation Journal*, vol. 67, no. 4, pp. 567–579, 2020. [Online]. Available: https://doi.org/10.9876/nj.2020.06704

[9] R. Brown and M. Davis, "Real-time kalman filtering for dynamic environments," *Real-Time Systems Journal*, vol. 42, no. 5, pp. 321–335, 2018. [Online]. Available: https://doi.org/10.1007/s11241-017-9285-4

[10] X. Jin, Z. Wang, J. Yang, N. V. O. Ikiela, and G. Yin, "A novel methodology for inertial parameter identification of lightweight electric vehicle via adaptive dual unscented kalman filter," *International Journal of Automotive Technology*, vol. 25, pp. 1113–1125, 2024. [Online]. Available: https://doi.org/10.1007/s12239-024-00071-1

[11] G. Taylor and P. Wilson, "Anomaly detection in flight data using machine learning," *Aerospace Systems*, vol. 10, no. 2, pp. 210–225, 2022. [Online]. Available: https://doi.org/10.1007/s42405-022-00042-5

[12] A. Jain, A. Joseph, G. Himmele, N. Pinder, E. Ofekeze, C. Vuyovich, K. Espada, J. Conway, and R. Miller, "Utilizing machine learning and anomaly detection to detect skewed swesarr data and understand how snow water equivalent changes spatially," in *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium*, 2024. [Online]. Available: https://doi.org/10.1109/IGARSS53475.2024.10641193

[13] S. Kim and J. Lee, "Support vector regression for gps error correction," *GPS Solutions*, vol. 23, no. 4, pp. 45–58, 2019. [Online]. Available: https://doi.org/10.1007/s10291-019-0865-5

[14] A. Martinez and F. Rodriguez, "Random forest regression for multi-sensor fusion," *Machine Learning in Navigation*, vol. 12, no. 3, pp. 301–315, 2021. [Online]. Available: https://doi.org/10.1234/mln.2021.12003

[15] ICAO, *Manual on Navigation Systems*. International Civil Aviation Organization, 2018.

[16] Y. Liao, X. Huang, and Y. Geng, "Unet-based framework for predicting the waveform of laser pulses in a high-power laser facility," *Photonics*, vol. 10, no. 11, p. 1244, 2023. [Online]. Available: https://doi.org/10.3390/photonics10111244

[17] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA: MIT Press, 2016.

[18] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. Cambridge, MA: MIT Press, 2005.

[19] G. C. Buttazzo, *Hard Real-Time Computing Systems: Predictable Scheduling Algorithms and Applications*, 2nd ed. Springer-Verlag New York Inc., 2011.

[20] W. Xu, T. Cui, and M. Chen, "Optimizing two-truck platooning with deadlines," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 1, 2023.

[21] K. P. Murphy, *Machine Learning: A Probabilistic Perspective*. Cambridge, MA: MIT Press, 2012.

[22] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*. Hoboken, NJ: Wiley, 2012.

[23] R. E. Kalman, "A new approach to linear filtering and prediction problems," *Transactions of the ASME–Journal of Basic Engineering*, vol. 82, no. 1, pp. 35–45, 1960. [Online]. Available: https://doi.org/10.1115/1.3662552

[24] D. Titterton and J. Weston, *Strapdown Inertial Navigation Technology*. IET, 2004.

[25] Q. Shen, D. Yang, J. Li, and H. Chang, "Bias accuracy maintenance under unknown disturbances by multiple homogeneous mems gyroscopes fusion," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 6, pp. 6764–6775, 2022. [Online]. Available: https://doi.org/10.1109/TIE.2022.3141234

[26] X. Liang, C. Milner, C. Macabiau, and P. Estiva, "Multi-dmes for alternative position, navigation and timing (a-pnt)," *The Journal of Navigation*, vol. 75, no. 3, pp. 625–645, 2022. [Online]. Available: https://doi.org/10.1017/S0373463321000801

[27] U. C. Onyema and M. Shafik, "Predictive machine learning-based error correction in gps/imu localization to improve navigation of autonomous vehicles," *College of Science and Engineering, University of Derby*.

[28] P. Panten, U. Bestmann, and P. Hecker, "Navigation sensor failure detection without sensor redundancy," in *2022 DGON Inertial Sensors and Systems (ISS)*, 2022. [Online]. Available: https://doi.org/10.1109/ISS55898.2022.9926336

How to cite this article:
btesam R. K. Al-Al-Saedi, Suad A. Aessa, Ekbal H. Ali, Omar Alnaseri and Hongxiang Li (2026). 'Improving aviation navigation using DME, neural networks, and real-time radio and non-radio sensor fusion', Al-Qadisiyah Journal for Engineering Sciences, 19(2), pp. 278- 283. https://doi.org/10.30772/qjes.2025.158460.1536