# Q-NAV: AI-Assisted Quantum Navigation For GPS-Denied Autonomous Systems

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***Abstract*—Systems for global navigation such as GPS are of great importance in enabling autonomous vehicles, drones, and robotic systems to navigate. Yet because these systems rely on external satellite signals, autonomous systems can be susceptible to signal obstruction, jamming, spoofing, and operation in areas where GPS is unavailable.**

***Although conventional Inertial Navigation Systems (INS) can offer navigation independent of external signals, they suffer from sensor noise accumulation and drift, which leads to a gradual increase in localisation errors over time. This study presents a hybrid navigation approach that combines quantum inertial sensing with an Artificial Intelligence (AI)-based error-correction and sensor-fusion method to enhance localisation accuracy in GPS-denied situations. The quantum inertial sensors, based on atom-interferometric principles, provide highly sensitive measurements of both acceleration and rotation, and the AI component is intended to learn to compensate for sensor noise, bias, and accumulated navigation drift. The framework will be tested through a simulation study that compares conventional inertial navigation, quantum-assisted navigation, and AI-assisted quantum inertial navigation under different noise levels and in GPS-denied conditions. Performance will be evaluated using position error, velocity error, orientation error, and navigation drift as the main indicators.***

***The objective of the proposed method is to show how combining emerging quantum sensing with intelligent computational methods can enable more reliable, high-precision autonomous navigation.***

***This research has potential applications in autonomous drones, intelligent transportation, robotics, and other safety-critical systems that need reliable positioning without relying continuously on satellite navigation.***

***Index Terms*—Quantum navigation, GNSS-denied navigation, inertial navigation system, quantum sensing, artificial intelligence, sensor fusion, atom interferometry, autonomous systems.**

## I. INTRODUCTION

Accurate positioning and navigation will be fundamental requirements for autonomous systems. Self-driving vehicles, UAVs, mobile robots, and intelligent transportation systems will require continuous information about their position, velocity, and orientation to perform route and decision-making tasks. GNSS will remain one of the most widely used technologies for providing global positioning information because it will allow autonomous systems to determine their location without requiring local positioning infrastructure [1], [6].

Despite these advantages, GNSS will not always be available or reliable. Buildings, mountains, tunnels, underground structures, and dense metropolitan environments can obstruct satellite signals. GNSS signals can also be intentionally disrupted through congestion or manipulated through spoofing attacks. These limitations create major challenges for autonomous systems that must operate reliably within safety-critical or infrastructure-limited environments [1], [7].

When GNSS becomes unavailable, autonomous systems will commonly depend upon Inertial Navigation Systems. An INS uses accelerometers and gyroscopes to estimate changes in velocity, position, and orientation. Because an INS does not require external radio signals during operation, it is suitable for GNSS-denied navigation. However, inertial measurements will contain sensor interference, bias, scale-factor errors, and other imperfections. These errors accumulate during computational integration, causing navigation drift to increase over time [6].

Quantum detection provides a possible approach to improving inertial navigation. Quantum inertial sensors will exploit quantum physical effects to measure acceleration and rotation with potentially high sensitivity and sustained stability. In particular, atom-interferometric sensors are promising for inertial navigation because their measurements can be linked to the phase progression of quantum particles [2], [3].

However, quantum sensors will not necessarily replace conventional inertial sensors. Practical quantum sensors will experience challenges related to measurement bandwidth, environmental sensitivity, system complexity, calibration, size, power consumption, and real-time operation. A combined quantum-classical architecture will thus provide a possibly more practical approach by combining the high-rate measurements of conventional IMUs with the extended stability of quantum sensing [2], [3].

Artificial Intelligence will provide additional opportunities to improve navigation performance. Machine-learning models can learn nonlinear relationships between sensor measurements and navigation errors. AI-based models will therefore be examined to estimate sensor bias, predict residual navigation errors, and compensate for accumulated drift.

Based on these considerations, this research will propose Q-NAV, an AI-assisted quantum-classical navigation framework for GNSS-denied autonomous systems. The proposed framework will combine conventional inertial sensing, quantum inertial sensing, sensor fusion, and AI-based error correction.

The major contributions of the proposed research will include:

1. A combined quantum-classical architecture for GNSS-denied autonomous navigation.
2. Integration of conventional IMU measurements with simulated quantum inertial measurements.
3. An AI-based mechanism for estimating residual navigation errors.
4. A simulation-based comparison of conventional INS, quantum-assisted INS, and Q-NAV.
5. Evaluation using position error, velocity error, orientation error, navigation drift, and RMSE.

## II. RELATED WORK

### *A. Conventional Inertial Navigation Systems*

Inertial Navigation Systems will be widely used in aerospace, automotive, maritime, military, and robotic applications. An INS will estimate the navigation state of a moving platform using accelerometer and gyroscope measurements. The main advantage of an INS will be its independence from external positioning infrastructure.

Nevertheless, inertial sensors will be affected by measurement noise, bias, scale-factor errors, and misalignment. Minor errors in acceleration and angular velocity will grow significant after repeated integration. As a result, the position and velocity estimates will gradually diverge from the actual trajectory. Conventional INS implementations will therefore generally require external measurements such as GNSS, visual information, LiDAR, or other navigation references to control long-term drift [6].

### *B. Quantum Inertial Sensing*

Quantum inertial sensing will use quantum mechanical phenomena to measure inertial quantities. Atom interferometry will be one of the important approaches in this field. In an atom-interferometric sensor, atomic matter waves will be manipulated using light pulses, and the resulting phase shift will be related to acceleration or rotation [2], [3].

Quantum inertial sensors provide high sensitivity and improved long-term stability. These properties will make them attractive for navigation applications where GNSS signals are unavailable. Research will also investigate cold-atom systems that will combine quantum sensing with orthodox inertial technologies to attain practical navigation performance [2].

### *C. Quantum Navigation*

Quantum navigation refers to navigation systems that use quantum sensors to improve Positioning, Navigation, and Timing capabilities. Quantum accelerometers, gyroscopes, gravity sensors, and magnetic-field sensors will be investigated for applications where conventional navigation references may become unavailable. A fully quantum-based navigation system may face feasible execution challenges. Hence, combined quantum-classical architectures will be considered more suitable for the proposed research. Such architectures will allow conventional sensors to provide high-frequency measurements, although quantum sensors will provide a more stable long-term reference [2], [3].

### *D. Artificial Intelligence in Navigation*

Artificial Intelligence and machine-learning methods will increasingly be applied to navigation, sensor calibration, localisation, and sensor fusion. Neural networks can learn nonlinear relationships between sensor measurements and navigation errors.

Sequential models such as Long Short-Term Memory networks will be particularly relevant because inertial-navigation errors evolve. AI-based methods will therefore be considered to estimate residual navigation errors and correct drift. Recent research will also investigate neural-network-based correction of quantum inertial navigation drift [10].

### *E. Research Gap*

Existing research demonstrates the capability of quantum inertial sensors for navigation and investigates AI-based navigation-error correction. However, integrating conventional inertial sensing, quantum inertial sensing, sensor fusion, and AI-based error correction into a unified simulation framework remains an important area for investigation.

The proposed Q-NAV framework will address this problem by developing a combined quantum-classical architecture in which AI serves as an additional error-correction layer.

## III. PROBLEM STATEMENT AND RESEARCH OBJECTIVES

### *A. Problem Statement*

Autonomous systems operating in GNSS-denied environments will need to rely on onboard sensors for continuous localisation. Conventional INS provides independent navigation, but measurement error and bias cause accumulated drift. Quantum inertial sensing may reduce long-term inertial errors, while AI may learn and compensate for residual navigation errors.

However, the combined effect of quantum sensing and AI-assisted error correction on GNSS-denied navigation performance will require systematic evaluation.

Therefore, the proposed research will investigate:

How will AI-assisted quantum-classical sensor fusion improve localisation accuracy and reduce navigation drift during prolonged GNSS-denied operation?

### *B. Research Objectives*

The objectives of this research will be:

1. To develop a simulation model of a conventional inertial navigation system.
2. To model quantum-enhanced inertial measurements.
3. To develop a quantum-classical sensor-fusion mechanism.
4. To design an AI-based navigation-error estimation model.
5. To evaluate the proposed Q-NAV framework under GNSS-denied conditions.
6. To compare Q-NAV with conventional and quantum-assisted navigation systems.
7. To measure navigation performance using standardised error metrics.

## IV. PROPOSED Q-NAV FRAMEWORK

### *A. Overall Architecture*

The proposed Q-NAV framework will consist of five major components:

1. Classical Inertial Measurement Unit.
2. Quantum Inertial Sensor.
3. Quantum-Classical Sensor Fusion.
4. AI-Based Error Correction.
5. Navigation-State Estimation.

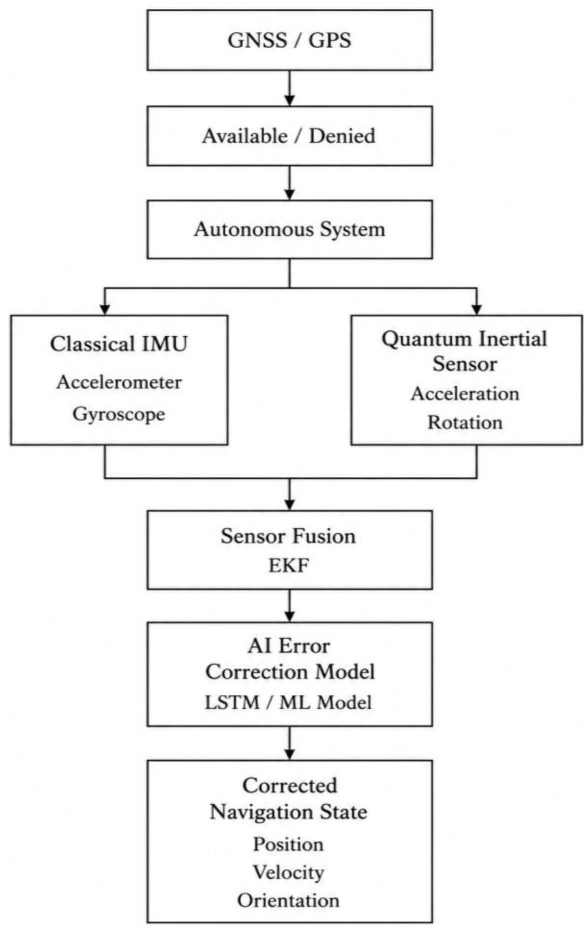


*Fig. 1. Proposed Q-NAV hybrid quantum-classical navigation framework.*

The classical IMU will provide high-frequency acceleration and angular-velocity measurements. The quantum sensor will provide complementary inertial measurements. The sensor-fusion layer will combine two measurement sources. The AI component will estimate residual navigation errors, and the corrected navigation state will provide the final position, velocity, and orientation estimates.

*B. Classical Inertial Measurement Unit*

The classical IMU will consist of three-axis accelerometers and three-axis gyroscopes. The accelerometers will measure specific force, while the gyroscopes will measure angular velocity.

The simulated IMU measurements will include:

- True acceleration.
- Accelerometer bias.
- Accelerometer noise.
- True angular velocity.
- Gyroscope bias.
- Gyroscope noise.

These measurements will be used to propagate the navigation state at a high update rate.

*C. Quantum Inertial Sensor*

The quantum sensing component will represent quantum-enhanced measurements of acceleration and rotation. Atom-interferometric sensing will be considered as the conceptual technology for the proposed model [2], [3].

The quantum sensor will provide an additional inertial reference. Its simulated measurement characteristics will be configured to represent improved prolonged stability compared with the conventional IMU.

*D. Quantum-Classical Sensor Fusion*

The measurements from the classical and quantum sensors will be combined using a state-estimation algorithm. An Extended Kalman Filter will be considered for estimating the navigation state and sensor biases.

The state vector will be represented as:

$$x = \left[p, v, q, b_a, b_g\right]^T$$

where will represent position, will represent velocity, will represent orientation, will represent accelerometer bias, and will represent gyroscope bias.

*E. AI-Based Error Correction*

The AI layer will be designed to learn relationships between sensor measurements and navigation errors.

Potential input parameters will include:

- Accelerometer measurements.
- Gyroscope measurements.
- Quantum acceleration measurements.
- Quantum rotational measurements.
- Estimated position.
- Estimated velocity.
- Sensor-bias estimates.
- Previous navigation residuals.

The AI model will estimate the residual navigation error as:

$$\hat{e}_k = f\theta(Z_{k-n:k})$$

where fθ will represent the trained AI model, and $Z_{k-n:k}$ will represent a sequence of recent sensor and navigation measurements.

The estimated error will subsequently be used to correct the navigation state.

## V. MATHEMATICAL MODEL

*A. Inertial Measurement Model*

The accelerometer measurement will be represented as:

$$a_m = a_{\{true\}} + b_a + n_a \qquad (1)$$

where will represent measured acceleration, will represent true acceleration, will represent accelerometer bias, and will represent measurement noise.

The gyroscope measurement will be represented as:

$$\omega_m = \omega_{true} + b_g + n_g \qquad (2)$$

where will represent measured angular velocity, will represent gyroscope bias, and will represent gyroscope noise.

*B. Velocity Update*

The navigation velocity will be updated using:

$$v_{k+1} = v_k + (R_k a_k - g)\Delta t \qquad (3)$$

where will represent the orientation transformation matrix, will represent gravitational acceleration, and will represent the sampling interval.

*C. Position Update*

The position will be updated using:

$$p_{k+1} = p_k + v_k\Delta t + \left(\frac{1}{2}\right)(R_k a_k - g)(\Delta t)^2 \qquad (4)$$

*D. AI Error Estimation*

The AI model will estimate the residual error using:

$$e_{hat_k} = f_{\theta(z_{k-n:k})} \quad (5)$$

The corrected navigation state will then be represented as:

$$x_{hat_{corrected}} = x_{hat_{raw}} - e_{hat} \quad (6)$$

## VI. PROPOSED SIMULATION METHODOLOGY

The Q-NAV framework will initially be evaluated through simulation-based testing.

The proposed simulation will produce a reference trajectory and corresponding sensor measurements before introducing GNSS-denied conditions. The overall simulation workflow will be organised as shown in Fig. 2.

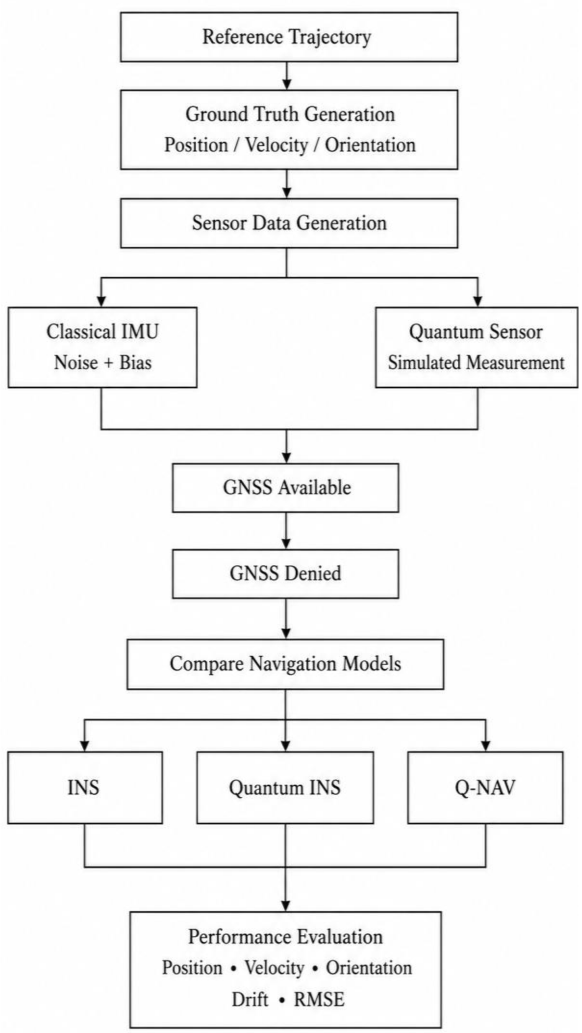


*Fig.2. Proposed simulation workflow for evaluating Q-NAV under GNSS-denied conditions*

*A. Reference Trajectory*

A predefined trajectory representing the motion of an autonomous vehicle or UAV will be generated. The trajectory will provide the ground-truth position, velocity, and orientation required for performance assessment.

*B. Sensor Data Generation*

Synthetic accelerometer and gyroscope measurements will be generated from the reference trajectory. Controlled noise and bias will be introduced to replicate realistic sensor imperfections.

Quantum inertial measurements will also be simulated using different noise and stability aspects.

*C. GNSS-Denied Scenario*

The simulation will begin with a GNSS-available phase to establish the initial navigation state. GNSS measurements will then be removed to create the GNSS-denied condition.

The navigation system will subsequently depend on inertial and quantum measurements.

*D. Experimental Configurations*

Three configurations will be evaluated.

Case 1: Conventional INS

The system will use only classical IMU measurements.

Case 2: Quantum-Assisted INS

The system will combine classical IMU measurements with quantum inertial measurements.

Case 3: Proposed Q-NAV

The system will combine:

Classical IMU + Quantum Sensor + Sensor Fusion + AI Error Correction

*E. Noise Conditions*

Different levels of sensor noise and bias will be introduced to evaluate each configuration's robustness.

## VII. PERFORMANCE EVALUATION

*A. Position Error*

Position error will be calculated as:

$$E_p = ||p_{estimated} - p_{true}|| \quad (7)$$

*B. Velocity Error*

Velocity error will be calculated as:

$$E_v = ||v_{estimated} - v_{true}|| \tag{8}$$

*C. Orientation Error*

Orientation error will be calculated by comparing the estimated orientation with the reference orientation.

*D. Navigation Drift*

Navigation drift will be evaluated by measuring the increase in position error as the GNSS-denied period becomes longer.

*E. Root Mean Square Error*

RMSE will be calculated as:

$$RMSE = sqrt\left(\left(\frac{1}{N}\right)\Sigma_{i=1}^{N} e_i^2\right) \tag{9}$$

*F. Comparative Evaluation*

The performance of the three configurations will be compared using:

- Position RMSE.
- Velocity RMSE.
- Orientation error.
- Navigation drift.
- Error growth over time.

## VIII. EXPECTED RESULTS AND DISCUSSION

*A. Expected Navigation Drift Behaviour*

Since the proposed Q-NAV framework will not yet be experimentally validated, the expected navigation-drift behaviour of the three approaches is presented conceptually.

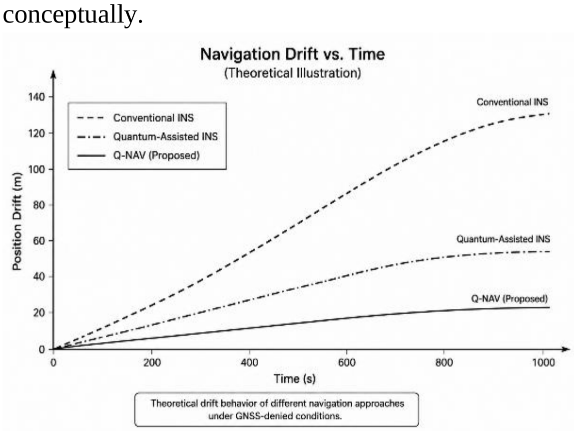


*Fig. 3. Theoretical navigation-drift behaviour of conventional INS, quantum-assisted INS, and the proposed Q-NAV framework under GNSS-denied conditions*

As illustrated in Fig.3, conventional INS will be expected to exhibit the highest drift, while quantum-assisted INS will be expected to reduce long-term drift. The proposed Q-NAV framework is expected to reduce residual navigation error through AI-based correction further.

These outcomes will be considered expected results until the proposed simulation is implemented and evaluated.

## IX. POTENTIAL APPLICATIONS

The proposed Q-NAV framework will have possible applications in:

1. Autonomous UAVs.
2. Autonomous ground vehicles.
3. GNSS-denied robotics.
4. Underground navigation.
5. Disaster-response systems.
6. Maritime autonomous systems.
7. Aerospace navigation.
8. Safety-critical autonomous systems.

## X. CONCLUSION

This research will propose Q-NAV, an AI-assisted quantum-classical navigation framework for autonomous systems operating in GNSS-denied environments. The proposed architecture will combine conventional inertial sensing, quantum inertial sensing, sensor fusion, and AI-based error correction to address the navigation drift associated with conventional INS.

The classical IMU will provide high-rate motion measurements, while the quantum sensor will provide a complementary inertial reference with potentially improved prolonged stability. The AI layer will estimate residual sensor and navigation errors and provide an additional correction mechanism.

A simulation-based methodology will be developed to compare conventional INS, quantum-assisted INS, and the proposed Q-NAV framework. Position error, velocity error, orientation error, navigation drift, and RMSE will be used as the primary evaluation criteria.

The proposed research will provide a basis for investigating the combination of quantum sensing technology and Artificial Intelligence for resilient autonomous navigation. More experimental work with real quantum measurement devices and autonomous platforms will be required to validate the practical performance of the proposed Q-NAV framework.

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