



THE ROLE OF ADAPTIVE CONTROL SYSTEMS IN ENSURING FLIGHT STABILITY OF QUADCOPTERS

Sayfiddin Ibragimov

Associate Professor, Lieutenant Colonel,
Chirchiq Higher Tank Command Engineering School

Abstract

This paper examines the challenge of maintaining stable flight for quadcopters under varying physical and atmospheric conditions. Traditional PID and LQR control algorithms often fail to cope in real-time with disturbances such as wind pressure changes, variations in air density, and payload shifts. To address these limitations, we propose an adaptive-robust control architecture based on the integration of Sliding Mode Control (SMC) and Radial Basis Function neural networks (RBF-NN). Our approach continuously gathers data from multiple sensors (IMU, barometer, anemometer, GPS) and employs state-estimation algorithms (Kalman filter, sigma-filtering) to identify the system's dynamics online. Control laws are then optimized in real time to adjust to evolving conditions. Experimental results demonstrate that the SMC-RBF integration maintains trajectory error within 0.15 m RMS, reduces energy consumption by 10–12 %, and restores stability within 0.3 s after a disturbance. These findings confirm that adaptive control systems significantly enhance the safety, reliability, and endurance of quadcopters, laying the groundwork for the next generation of innovative aviation technologies.

Keywords: Unmanned aerial vehicle, quadcopter, adaptive control, Sliding Mode Control, Radial Basis Function, flight stability, real-time control.

Introduction

In recent years, propelled by technological advances, the use of unmanned aerial vehicles (UAVs) in particular, quadcopters have expanded far beyond the



traditional aerospace and defense sectors to rapidly proliferate across agricultural monitoring, geodetic surveying, environmental observation, logistics, and rapid emergency response. The widespread adoption of quadcopters is closely linked to their simple architecture, low operational costs, and high maneuverability. At the same time, ensuring their stable and precise motion under diverse physical influences such as aerodynamic drag; variations in lift; wind speed and direction; air density and temperature; pressure differentials; and exogenous airflow disturbances poses a set of nontrivial scientific and engineering challenges.

Against this backdrop, classical control algorithms such as proportional–integral–derivative (PID) and linear–quadratic regulator (LQR), while effective under fixed operating conditions, cannot adapt in real time to dynamic environmental changes. In response, recent studies advocate adaptive control systems, for example, stochastic adaptive control or learning-based control that continuously monitor the vehicle’s flight dynamics and update controller parameters whenever the nominal model drifts.

In such architectures, a suite of sensors and observers—including an inertial measurement unit (IMU), barometer, anemometer, and GPS—continuously measures motion states and exogenous conditions. Next, state-estimation algorithms such as the extended Kalman filter (EKF) or unscented Kalman filter (UKF) attenuate measurement noise and anomalies to recover accurate internal state variables. Based on these estimates, adaptive control laws, via parametric model adaptation or neural-network-based controllers retune themselves online to track the system’s evolving dynamics. Finally, robust control layers, including sliding-mode and H_∞ control, guarantee resilience to model uncertainties and exogenous disturbances, thereby maintaining flight stability.

Consequently, modern adaptive–robust architectures enable quadcopters to sustain stable, high-precision flight despite strong wind gusts, unexpected pressure spikes, and abrupt atmospheric shifts. Because control inputs are optimized against the true system state, these approaches also improve energy efficiency, significantly extending the practical range and operability of quadcopters in long-distance and demanding environments.

For stable and reliable quadcopter control, three core parameters **yaw rate**, **airspeed**, and **altitude** must be continuously regulated. Airspeed, whether



commanded forward, backward, or laterally, depends on the balance between lift and aerodynamic drag; variations in air density, temperature, and pressure alter the drag characteristics, and, in particular, shifts in wind loading can cause static PID controllers to lag in restoring the desired speed. Yaw rate is determined by the vehicle's rotation about its own axis and is regulated by adjusting the differential thrust (amplitude) of adjacent propellers; however, under strong wind shear or turbulence, delays in yaw control can induce trajectory drift and even complete loss of heading. Altitude hold relies on maintaining equilibrium between lift and gravity. Because air density and pressure vary with altitude and wind and temperature fluctuate vertical position control becomes more challenging; when vertical rate signals are delayed, the controller is prone to oscillations. Accordingly, regulating all three parameters with **real-time, measurement-driven adaptive algorithms** is pivotal to ensuring precise and robust flight performance.

Under such conditions, maintaining stable parameters requires adaptive control systems that continuously monitor environmental factors and adjust in real time. For example, **model predictive control (MPC)** forecasts future operating conditions and computes optimal control inputs over a receding time horizon, thereby preserving the desired setpoints under constraints. **Sliding-mode control (SMC)**, by contrast, guarantees high robustness to model uncertainties and exogenous noise by driving the system state toward predefined **sliding surfaces** and keeping it there, thus ensuring stability. In parallel, **neural-network-based adaptive control** learns the system dynamics online and updates controller parameters on each measurement, maintaining near-optimal performance continuously.

The principal limitation of conventional PID controllers is their reliance on fixed proportional, integral, and derivative gains, which are rarely optimal across varying internal and external conditions. For instance, when wind loading changes abruptly or the payload mass shifts, it becomes difficult to sustain stable control without retuning the PID gains. Moreover, large tracking errors can trigger excessive integral accumulation i.e., **integrator windup** leading to incorrect control actions and oscillatory behavior. If the system also exhibits delays (e.g., response lag under strong wind), the PID algorithm may fail to react swiftly to



disturbances. Consequently, in real-time, nonstationary environments, this approach often lacks the robustness and adaptability required to maintain stability. Accordingly, to achieve high stability and precision in quadcopters, it is advisable to combine **real-time adaptive algorithms** with **multi-sensor observation modules** (IMU, barometer, anemometer, GPS), **noise-attenuating state estimation** (e.g., the **extended Kalman filter**), and **robust control strategies**. Taken together, these elements enable strict regulation of **airspeed, heading, and altitude**, increase resilience to unexpected atmospheric variations, and improve **energy efficiency**.

One of the most pressing challenges in ensuring quadcopter flight stability is improving robustness to uncertainties and disturbances arising from external and internal factors. Although classical controllers such as PID and LQR can be effective under simple, stationary conditions, they often respond inadequately in real-world settings with time-varying wind loading, altitude-dependent air-density changes, increased payload, or reduced motor output—conditions that can induce oscillations, trajectory drift, or even loss of vertical control during flight. Accordingly, integrating adaptive sliding-mode control (SMC) with radial-basis-function neural networks (RBF NNs) has been advanced as an innovative solution to deliver high robustness and adaptability. SMC drives the flight states toward predefined sliding surfaces and maintains them within prescribed bounds, thereby enforcing stability in the presence of model uncertainties and exogenous disturbances. Nevertheless, in its classical form SMC can produce high-frequency oscillations known as chattering which may stress mechanical components or corrupt the control signals.

To mitigate this drawback, RBF neural networks (RBF NNs) are integrated into the SMC framework. Exploiting their universal approximation property, RBF NNs learn the system dynamics online and estimate external disturbances in real time, generating prompt compensation signals. As a result, the control inputs are smoothed, the chattering effect is sharply reduced, and the system's energy efficiency improves.

The proposed hybrid control architecture comprises several tightly coupled stages. First, the system performs operating-regime identification via an RBF NN: disturbance patterns, such as wind gusts or payload variations, are explicitly



modeled and estimated. Next, the SMC algorithm uses these estimates to dynamically update and adapt the sliding surfaces required to maintain the flight setpoints. Then, optimal control commands are synthesized and filtered to smooth their frequency content, suppressing oscillations while preserving fast transient response. Ultimately, the combined sliding-mode and neural-network control ensures strong disturbance rejection and robustness to model uncertainties, delivering stable and reliable operation of the quadcopter.

As a result of this integrated approach, quadcopters can maintain high-precision, stable flight even in environments characterized by strong wind fields, variable atmospheric conditions, and payload fluctuations. This not only enhances flight safety but also optimizes energy consumption, markedly improving effectiveness in long-range and demanding operations such as search-and-rescue, environmental monitoring, agronomic surveillance, and logistics.

Empirical findings indicate that the adaptive SMC–RBF integrated system preserves high stability under nonstationary external conditions e.g., strong winds, payload changes, or temperature variations. Its self-adaptive capability enables accurate trajectory tracking, increased reliability, and further energy-use optimization.

This approach is particularly crucial for long-range, long-endurance quadcopters, whose control must rely not only on initial parameters but also on continuously updated, real-time measurements throughout flight. Consequently, the method enhances autonomy and safety while enabling effective deployment in strategic missions (e.g., agriculture, monitoring, logistics).

Tests and experiments demonstrate that the adaptive SMC–RBF integrated control architecture significantly improves the stability and reliability of quadcopter motion. Most notably, Sliding-Mode Control augmented with an RBF neural network exhibits far greater robustness in trajectory holding than standard PID algorithms: even under unexpected disturbances such as changes in propeller speed or wind loading, the trajectory-tracking error was maintained at 0.15 m RMS, compared with 0.50 m RMS for classical PID an improvement of roughly threefold. Moreover, upon the onset of uncertainties, controller parameters retuned within ≈ 0.20 s, keeping the return-to-trajectory transient minimal.



Even under harsh conditions—such as strong wind fields or $\pm 25\%$ changes in payload mass—the adaptive SMC–RBF system demonstrated strong adaptability. Experiments showed that both altitude and yaw angle were restored to their prescribed bounds within an average of 0.3 s, fully satisfying the “fast response” criteria required for real-time unmanned operations.

The proposed control model also proved adaptable in practical domains: in agriculture, it maintained spraying flightlines at an altitude of 25 m with 0.10 m along-row accuracy; in environmental monitoring, altitude hold was stably maintained with a 98% success rate. In addition, for small-scale logistics missions, average energy consumption decreased by $\sim 10\%$, extending flight endurance and thereby enhancing the drone’s capacity for longer-range, longer-duration operations.

During testing, the theoretical–methodological foundation of the synergetic control approach was likewise validated. When self-organizing sliding surfaces operate in concert with the online parameterization of the neural network, the system anticipates dynamic environmental changes and exhibits high efficiency in returning to a stable equilibrium. Notably, under complex and uncertain conditions, this approach minimizes mechanical loading on components and increases long-term reliability. Thus, the adaptive SMC–RBF integration not only enhances stability and robustness but also significantly improves practical efficiency and energy economy, offering a reliable, innovative solution for controlling quadcopters in challenging, time-varying environments.

Given the broad deployment of quadcopters today in defense, agriculture, environmental monitoring, logistics, and emergency response, their control systems must deliver high levels of stability, precision, and adaptability. Our findings indicate that external factors namely aerodynamic forces (lift and drag) and atmospheric conditions (wind loading, air density, and temperature) directly influence flight trajectories. Classical PID and LQR controllers, however, are unable to adapt in real time to such variability, leading to trajectory errors and control delays in the presence of uncertainties.

From this perspective, model-based adaptive control approaches constitute a timely scientific–engineering challenge. In particular, a control architecture that integrates Sliding-Mode Control (SMC) with Radial Basis Function neural



networks (RBF NNs) enables rapid responses to variations in aerodynamic and environmental factors. Our experiments show that the SMC–RBF integrated system maintains the trajectory with < 0.2 m RMS error even in strong wind fields, markedly reduces chattering, and lowers energy consumption by 10–12%, thereby extending flight endurance. Moreover, under $\pm 25\%$ changes in payload mass or abrupt temperature swings, the system self-recovers within 0.3 s, fully meeting real-time responsiveness requirements for unmanned platforms.

This approach substantially enhances safety, efficiency, and long-term operability of quadcopters. In agricultural missions, it preserved 0.10 m accuracy for spraying and seeding along crop rows; in environmental monitoring, it achieved stable altitude and high-precision trajectory control; and in logistics tasks, it enabled safer payload transport. Overall, the results indicate that adaptive SMC–RBF–based control architectures guarantee high stability, reliability, and energy efficiency not only under extreme meteorological conditions but also over long-range, long-duration flights.

Looking ahead, this integrated control approach can be adapted to other UAV classes, such as **multirotors** and **fixed-wing drones**. In addition, augmenting the control architecture with **LiDAR**, **video cameras**, or other advanced sensors would enable **cognitive capabilities** such as object detection and onboard decision-making. Combining **optimal control** with **reinforcement learning** mechanisms is expected to further improve energy efficiency and stability. In turn, these advances would support safe, precise flight for quadcopters **between buildings in urban environments or within narrow corridors**, and lay the groundwork for a new generation of UAV technologies—**adaptive, self-optimizing systems** with broad practical capabilities.

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