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Deterministic and Stochastic Matrix Modeling of Radiophysical Processes in UAV Microcontroller Systems

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Abstract

This paper presents deterministic and stochastic matrix models for radiophysical processes in UAV microcontroller systems. The methodology generalizes matrix signal dynamics using Markov switchings and Ornstein–Uhlenbeck diffusion approximation. Based on oscilloscope measurements of the power supply voltage, model parameters were identified, revealing increased fluctuation intensity under higher propulsion loads. The results enable quantitative stability assessment of control algorithms. The key contribution is the combination of the matrix modeling approach with experimental identification of stochastic parameters under realistic electromagnetic interference conditions.

KEY WORDS: *UAV; radiophysical processes; stochastic differential equations; stochastic models; Markov switching; diffusion approximation; Ornstein–Uhlenbeck process; multi-scale stochastic systems.*

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1. **Introduction**

The rapid development and widespread deployment of unmanned aerial vehicles (UAVs) in both civilian and military sectors have placed unprecedented demands on the reliability of their onboard electronic systems [1,2]. Modern UAVs are complex cyber-physical systems where the microcontroller unit (MCU) acts as the central node, processing high-frequency sensor data and executing real-time control algorithms [3,4]. The operational stability of these systems is a critical factor, especially in challenging environments characterized by high electromagnetic interference (EMI) and fluctuating mechanical loads.

The mathematical modeling of radiophysical processes in microcontroller-based systems of UAVs is a fundamental task for ensuring this stability. Traditionally, such processes have been described using deterministic models. These models are capable of capturing the basic dynamics of key signal parameters, such as amplitude, phase, and power, under ideal or controlled conditions. However, deterministic approaches often fail to account for the complexities of real-world operating environments. Experimental evidence suggests that signals within UAV systems exhibit significant fluctuations, phase noise, and random deviations. These phenomena are primarily driven by unstable power supply levels, digital crosstalk between high-speed components, and the intense electromagnetic fields generated by the propulsion system's brushless DC motors (BLDC). Existing research in the field of stochastic systems, notably by Korolyuk, Samoilenko, and Chabanyuk [5, 7], provides a robust theoretical framework for analyzing evolutionary systems under random perturbations. While many studies treat noise as a simple additive Gaussian white noise, real-world UAV transients are better described as multi-scale processes with discrete switchings between different operational states. These stochastic effects cannot be adequately represented by purely deterministic equations, necessitating a transition to a more sophisticated stochastic modeling framework.

In this study, we propose a methodology that bridges the gap between theoretical matrix modeling and experimental data. First, a deterministic matrix model for signal dynamics is established. Subsequently, we justify the incorporation of random perturbations modeled as fast Markov switching processes. We demonstrate that in the asymptotic limit, these perturbations lead to a diffusion-type stochastic differential equation of the Ornstein–Uhlenbeck form [6]. This process is particularly suitable for modeling "return-to-mean" behavior in power supply fluctuations under load.

The primary objective of this work is to identify the parameters of the resulting stochastic model through empirical oscilloscope measurements of the power supply voltage in a UAV microcontroller system. By analyzing the system under varying propulsion loads (from idle to high thrust), we aim to provide a quantitative basis for assessing how electrical noise intensity influences the reliability of control algorithms.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 describes the mathematical background of matrix modeling and the diffusion approximation. Section 4 details the experimental setup and the methodology for data collection. Section 5 presents the identification of stochastic parameters and discusses the results. Finally, Section 6 concludes the paper with suggestions for future research.

2. Literature Review and Related Works

The analysis of signal stability in UAV systems has traditionally been dominated by deterministic control theory. However, the increasing complexity of flight missions and electronic interference environments has led researchers toward stochastic modeling. The foundational work on Ornstein–Uhlenbeck processes by Uhlenbeck and Ornstein [6] established a framework for modeling systems that exhibit a "return-to-mean" property, which is characteristic of voltage regulation in microcontrollers. Recent advancements by Korolyuk and Chabanyuk [5, 7] have introduced multi-scale asymptotic analysis, allowing for the simplification of complex Markov switching systems into continuous diffusion processes. In the context of UAVs, most contemporary studies focus on high-level sensor fusion (e.g., Extended Kalman Filters) to mitigate noise. However, these studies often assume that the underlying noise is stationary Gaussian white noise, whereas real radiophysical processes in embedded digital systems are known to exhibit non-stationary phase noise and power-related fluctuations driven by switching electronics. Our work differs from existing literature by directly linking the physical propulsion load (ESC switching and motor induction) to the stochastic parameters α and σ of the microcontroller's power supply, providing a bottom-up approach to system reliability.

3. The Mathematical Background

3.1. Deterministic Matrix Model of Signal Dynamics

The foundational representation of the radiophysical processes within the UAV microcontroller system is based on a state-vector approach. We define the state of the system at any given time *t* by a vector:

$$u(t) = \begin{pmatrix} A_s(t) \\ \phi(t) \\ P(t) \end{pmatrix}$$

where $A_s(t)$ represents the signal amplitude, $\phi(t)$ is the phase, and $P(t)$ denotes the instantaneous power consumption or supply voltage level.

The evolution of this system in a deterministic environment is governed by a linear differential equation:

$$\frac{du(t)}{dt} = Cu(t)$$

where

$$C = \begin{pmatrix} -\alpha(t) & 0 & 0 \\ 0 & \omega(t) & 0 \\ \beta(t) & 0 & \gamma(t) \end{pmatrix},$$

$\alpha(t)$ is a signal amplitude damping coefficient;$\omega(t)$ is an instantaneous angular frequency of the carrier;
$\gamma(t)$ is power loss coefficient in the receiving tract; $\beta(t)$ is coupling factor between signal amplitude and power.

Note: In the subsequent experimental identification (Section 5), the scalar Ornstein–Uhlenbeck relaxation parameter α corresponds to the diagonal element γ(t) of matrix C governing the power-supply component P(t), and should not be confused with the signal amplitude damping coefficient α(t) in the first row of C.

3.2. Averaging Scheme

The evolutionary system with random perturbations in a series scheme with a small parameter $\varepsilon \to 0$ ($\varepsilon > 0$) is given by the solution of the evolutionary equation:

$$\frac{du^\varepsilon(t)}{dt} = C\left(u^\varepsilon(t), x\left(\frac{t}{\varepsilon}\right)\right), t \geq 0 \quad (1)$$

where the velocity function $C(u; x)$, $u \in \mathbb{R}^d$, $x \in X$.

It is assumed that there exists a solution to the family of equations:

$$\frac{du_x(t)}{dt} = C(u_x(t), x), x \in X \quad (2)$$

Random perturbations are defined by a Markov jump process $x(t)$, $t \geq 0$, in a standard phase space $(X, \mathcal{F})$, given by a generating operator (generator) Q in the Banach space $\mathbb{B}(E)$ of test functions $\varphi(x) \in \mathbb{B}(E)$:

$$\mathbf{Q}\varphi(x) = q(x) \int_E P(x, dy)\,[\varphi(y) - \varphi(x)]$$

The stochastic kernel $P(x, B)$ defines a uniformly ergodic embedded Markov chain $x_n = x(\tau_n)$ with a stationary distribution $\rho(B)$.
The stationary distribution $\pi(B)$ of the Markov process $x(t)$ is determined by the relation:

$$\pi(dx)q(x) = q\rho(dx), q = \int_X \pi(dx)q(x)$$

Averaging Principle. If the Markov perturbation process $x(t)$ is uniformly ergodic with a stationary distribution $\pi(B)$, then under the conditions formulated above, there is a weak convergence:

$$u^{\varepsilon}(t) \xrightarrow{d} u^0(t), \varepsilon \to 0$$

The limit evolution $u^0(t)$is determined by the solution of the deterministic evolutionary equation:

$$\frac{du^0(t)}{dt} = \hat{C}(u^0(t)), t \geq 0$$

where the averaged velocity function is defined by the relation:

$$\hat{C}(u) = \int_E \pi(dx)C(u; x)$$

3.3. Diffusion Approximation

Balance condition for the dynamic system:

$$\hat{C}(u) = \int_E \pi(dx)C(u; x) \equiv 0$$

Under the balance condition, the averaged system maintains a constant value over an infinite time interval.
In this regard, the problem of studying the fluctuations of the dynamic system arises, which under balance conditions should be considered with the following normalization:

$$\frac{du^{\varepsilon}(t)}{dt} = \varepsilon^{-1} C\left(u^{\epsilon}(t), x\left(\frac{t}{\varepsilon^2}\right)\right) (3)$$

Diffusion approximation of the dynamic system. If the Markov perturbation process $x(t)$is uniformly ergodic with a stationary distribution $\pi(B)$, then under the balance condition, there is a weak convergence:

$$u^{\varepsilon}(t) \xrightarrow{d} \zeta^0(t), \varepsilon \to 0$$

The limit diffusion process $\zeta^0(t)$ is defined by the generator:

$$\mathbb{L}\varphi(u) = b(u)\varphi'(u) + \frac{1}{2}B(u)\varphi''(u) (4)$$

where:

$$b(u) = \int_X \pi(dx)b(u; x), b(u; x) = C(u; x)R_0C'_u(u; x) (5)$$

$$B(u) = \int_X \pi(dx)B(u; x), B(u; x) = C(u; x)R_0C(u; x) (6)$$

and the potential of the ergodic Markov process is:

$$R_0 = \int_0^{\infty} [\exp(Qt) - \Pi]\, dt$$

Note.
The limit diffusion process $\zeta^0(t)$is also given by the solution of the stochastic differential equation:

$$d\zeta^0(t) = b(\zeta^0(t))\, dt + \sigma(\zeta^0(t))\, dW(t)$$

where

$$\sigma^2(u) = B(u)$$

and $W(t)$ is a standard Wiener process.

4. Experimental Setup, Methodology, and Preliminary Analysis

4.1. Hardware Configuration and UAV Platform

To validate the proposed stochastic model, an experimental study was conducted using a 7-inch frame quadcopter platform. The vehicle is equipped with the SpeedyBee F405 V3 stack, featuring an STM32F405 microcontroller as the primary flight management unit. This MCU is responsible for real-time sensor fusion and executing PID control loops, making it highly sensitive to power supply quality.

The propulsion system comprises high-torque 2807 1300KV brushless motors, which are typical for long-range and heavy-lift UAVs. These motors, driven by a 50A ESC (Electronic Speed Controller), generate significant back-electromagnetic fields (back-EMF) and high-frequency switching noise. The radio link is maintained via an ELRS 915 MHz receiver, operating in a frequency band that requires precise voltage stabilization to avoid signal jitter. Power is supplied by a 6S1P Lithium-Polymer (LiPo) battery (22.2V nominal), providing the high-energy density required for the propulsion system but also increasing the amplitude of voltage ripples under load.

4.2. Measurement Instrumentation

Voltage fluctuations within the microcontroller’s power delivery network were captured using the FNIRSI DS215H digital storage oscilloscope. The device features a 200 MHz analog bandwidth and a 500 MS/s real-time sampling rate, which is more than sufficient to detect the fast transients caused by the 1300KV motors and the ESC switching cycles.

To isolate the stochastic component from the constant DC offset, the oscilloscope was set to AC-coupling mode. This allowed for a high-resolution analysis of millivolt-scale fluctuations (ripples). The probe was connected to the 5V/3.3V power rails directly at the MCU pins to ensure that the measured data reflected the actual noise environment of the digital logic. A sampling frequency of 1 MHz was maintained during data logging to capture the detailed structure of the "jumps" and noise bursts, forming the basis for subsequent parameter identification of the Ornstein–Uhlenbeck process.

4.3. Experimental Procedure and Load Profiles

The experiment was designed to observe the transition of stochastic parameters under different operational states. Four distinct load profiles were defined based on the propulsion system's power output:

a) **Idle State (0% load):** All motors are disarmed; only the MCU and onboard sensors are active. This represents the baseline thermal and digital noise.
b) **Low Thrust (5% load):** Motors spinning at minimum speed; initial induction of electromagnetic interference.
c) **Medium Load (10% load):** An intermediate load; motors at low operational speed with increased EMI.
d) **High Load (40% load):** Represents rapid maneuvering or climbing, where the ESCs operate at high duty cycles.

In addition to the four steady-state profiles, an auxiliary transient recording was performed using a 0%→20%→0% load profile (Fig. 5). This intermediate profile was designed specifically to capture a well-defined voltage relaxation transient for identification of the relaxation parameter α of the Ornstein–Uhlenbeck process.

For each state, a continuous time-series of voltage data was recorded. These data points were then used to calculate the statistical moments required for identifying the drift (α) and diffusion (σ) coefficients of the Ornstein–Uhlenbeck process.

4.4. Analysis of Stability and Error Probability

The identified parameters α and σ allow for a quantitative assessment of the system's stationary variance. For an Ornstein–Uhlenbeck process, the steady-state variance V is defined as: $Var\infty = \frac{\sigma^2}{2\alpha}$,

Using the experimental data for the 40% load ($\alpha = 63.0\ s^{-1},\ \sigma = 632.0 \cdot 10^{-3}\ V \cdot s^{-1}/^2$), the calculated variance is significantly higher than that of the idle or low-load states. This increase in variance directly affects the probability of the supply voltage crossing a critical reliability threshold V_{crit}.

The probability that the fluctuation U_t exceeds a threshold δ can be estimated using the properties of the Gaussian stationary distribution:

$$P(|U_t| > \delta) = 2 \int_{\delta}^{\infty} \frac{1}{\sqrt{2\pi Var\infty(U)}} \exp(-\frac{x^2}{2Var\infty(U)}) dx$$

As σ increases with the propulsion load, this probability increases nonlinearly. In practical terms, this means that while the system might appear stable on average, the frequency of transient “glitches” that can cause sensor data corruption or MCU brown-out resets increases drastically under high-thrust maneuvers.

4.5. Spectral Interpretation and Hardware Mitigation Strategies

While the Ornstein–Uhlenbeck process provides a macroscopic stochastic description of the noise, its physical origins are rooted in the high-frequency switching of the Electronic Speed Controllers (ESCs). The ESC switching frequencies (typically in the range of 24–48 kHz) are expected to produce dominant spectral peaks in the power supply noise, acting as the primary physical drivers of the Markov switching process $x(e/\epsilon)$.

To mitigate the identified diffusion intensity σ, the implementation of low-ESR (Equivalent Series Resistance) electrolytic capacitors is crucial. Mathematically, adding a capacitor increases the system's "electrical inertia," which directly correlates to an increase in the relaxation parameter α. A higher α ensures that any stochastic "jump" in voltage is suppressed more rapidly, returning the system to its equilibrium state U_0 before it can trigger an MCU logic error.

The experimental identification of $\alpha = 63.0\ s^{-1}$ suggests that for the SpeedyBee F405 V3 stack under the load of 2807 motors, the existing filtration is at its limit. For mission-critical UAVs, we recommend a hardware-software co-design approach: increasing physical capacitance to boost α while simultaneously tuning the digital low-pass filters in the flight controller to account for the identified σ levels.

5. Investigation Results and Parameter Identification

5.1. Analysis of Steady-State Oscillograms

The experimental data obtained via the FNIRSI DS215H oscilloscope demonstrates a statistically significant correlation between the propulsion system load and the intensity of stochastic fluctuations in the MCU power supply.

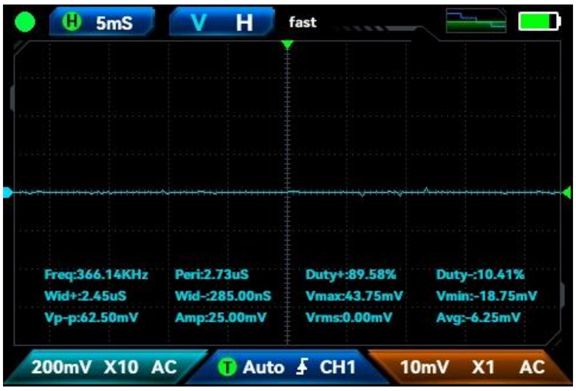

Fig. 1. The Oscilloscope waveform of MCU supply voltage ripple under idle conditions (0% load).

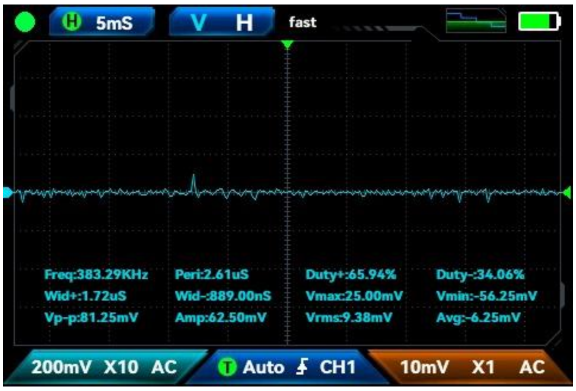

Fig. 2. The Supply voltage ripple at 5% propulsion load.

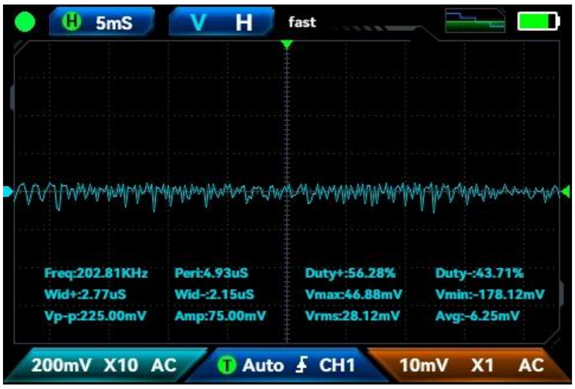

Fig. 3. The Supply voltage ripple at 10% propulsion load.

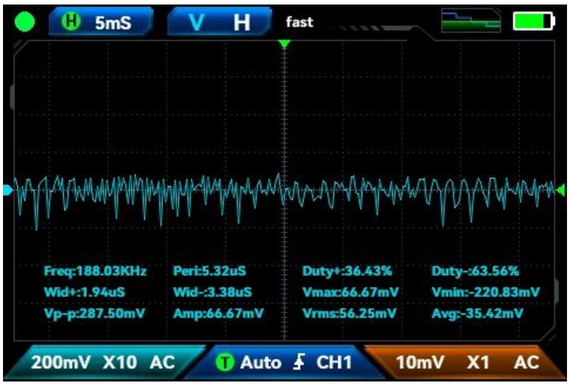

Fig. 4. The Supply voltage ripple at 40% propulsion load.

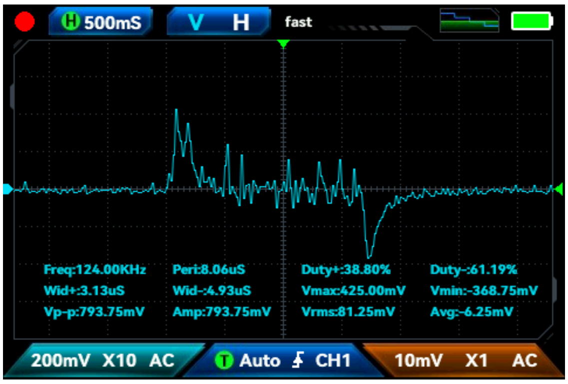

Fig. 5. The Transient response of MCU supply voltage during load transition: 0% → 20% → 0%.

Table 1. Oscillographic measurement results under four load conditions. * Amp: peak amplitude as measured by the oscilloscope.

Load	**Vpp, mV**	**Amp, mV ***	**Vrms, mV**	**Grade of Vrms**	**Type of process**
Motors is off	62.5	25.0	~0	V_0	Quasi-stationary noise
At 5% Load	81.3	62.5	9.38	$V_1 > V_0$	Gaussian process
At 10% Load	225.0	75.0	28.1	$V_2 \gg V_0$	Stationary stochastic process
At 40% Load	287.5	66.7	56.3	$V_3 \gg V_2$	Diffusion process

Analysis of oscillographic measurements of the supply voltage showed that with increasing load, the intensity of the stochastic component of the process increases significantly. In the operating modes of the propulsion system, a transition from almost stationary Gaussian noise to processes with impulse disturbances is observed, which justifies the use of stochastic models with diffusion and jump components.

In the case where the signal dynamics is described by a time system of differential equations, and the randomness of the environment is modeled by a switching process $x(t)$, the system takes the form

$$\frac{du(t)}{dt} = C(x(t), u(t)),$$

Assuming that the process $x(t)$ is ergodic and has a stationary measure, it is possible to average the dynamics over this measure. In the limit of fast switching of a random medium, fluctuations around the averaged motion give rise to a diffusion term, and the system is described by a stochastic differential equation of the type

$$dU(t) = C(u(t))dt + \sum(u(t))dW(t)$$

where the matrix $\Sigma(u)$ determines the intensity of stochastic disturbances arising from the random nature of the medium.

For the scalar power-supply component P(t), the diffusion matrix reduces to a scalar coefficient: $\Sigma^2(u) = B(u) = C(u;x)R_0C(u;x)$ (see eq. (6)), where $\sigma^2 = B(u)$. This is the scalar σ identified experimentally below.

The effect of stochastic disturbances on the state of the system can be quantitatively described within the framework of the Ornstein–Uhlenbeck model for the supply voltage.

$$U(t): dU(t) = -\alpha(U - U_0)dt + \sigma dW(t)$$

In such a formulation, the mean value is determined by the deterministic part, while the variance of deviations increases proportionally to $\sigma 2$ and in the stationary regime is equal to $Var_\infty(U) = \frac{\sigma 2}{2\alpha}$

To quantitatively confirm the obtained relationships, oscillographic measurements of the supply voltage of the UAV microcontroller system were carried out during a step change in the load.

In Fig. 5, the measurement was performed in AC-coupling mode, which allows for direct analysis of voltage fluctuations relative to the average level U_0, which in this case is taken to be zero. It should be noted that in the OU model $dU = -\alpha(U - U_0)dt + \sigma dW(t)$, the variable U represents the deviation of the supply voltage from its nominal level U_0 (5V or 3.3V), not the absolute voltage. The AC-coupling mode directly isolates this deviation, so the measured signal corresponds precisely to U in the model, with $U_0 = 0$ in the experimental frame of reference.

After the thrust is released, a characteristic process of voltage relaxation to the stationary level is observed, which has an exponential nature and can be approximated by the dependence $|U(t)| = | U(0) | e^{-\alpha t}$

Several characteristic points were selected from the oscillogram in the area of smooth voltage recovery after thrust release. The absolute values of voltage deviations and the corresponding time points are given below:

t=0 ms, |U| = 368 mV, t=10 ms, |U|= 200 mV, t=25 ms, |U|= 80 mV, t=35 ms, |U|= 40 mV,

The final point t=50ms, |U|=6 mV is at the noise background level and is not used to estimate the relaxation parameter. Linear approximation of the dependence of ln|U(t)| on time in the interval 0-35ms allowed us to estimate the parameter α. The identified value $\alpha = 63.0\ s^{-1}$ is treated as a structural constant of the power delivery network (PDN), since it is determined by the passive components of the circuit — primarily the equivalent capacitance and resistance of the power rails — rather than by the active propulsion load. Consequently, the same α is applied uniformly across all load profiles when computing σ from the measured Vrms values.

The diffusion coefficient σ is identified from the measured Vrms via the stationarity condition of the OU process (Table2). Since the stationary standard deviation equals $\sigma/\sqrt{(2\alpha)}$, and the oscilloscope measures $Vrms = \sigma/\sqrt{(2\alpha)}$, the correct identification formula is: $\sigma = Vrms\cdot\sqrt{(2\alpha)}$, where Vrms is expressed in volts (V). Note that in the continuous-time OU equation $dU = -\alpha(U-U_0)dt + \sigma dW(t)$, the dimensional analysis requires $[\sigma] = V\cdot s^{-1/2}$ (since $[dW] = s^{1/2}$). The numerical values below are therefore given in $V\cdot s^{-1/2}$. With $Vrms(10\%) = 28.1\cdot10^{-3}$ V, $Vrms(40\%) = 56.3\cdot10^{-3}$ V, and $\sqrt{(2\cdot63.0)} = 11.22$, this yields $\sigma = 315.6\cdot10^{-3}\ V\cdot s^{-1/2}$ (10% load) and $\sigma = 632.0\cdot10^{-3}\ V\cdot s^{-1/2}$ (40% load).

Table 2. Identified parameters of the stochastic supply voltage model.

Parameter	Value
σ (At 10% $load$)	$315.6\cdot10^{-3} V\cdot s^{-1}$, ; $632.0\cdot10^{-3}\ V\cdot s^{-1/2}$ (40% load)
α (from 20% load transient, Fig. 5)	63.0 s^{-1}
$\tau = \frac{1}{\alpha}$	15.873 ms
Stationary dispersion $Var_\infty(U)$	$\sigma^2/2\alpha$= $7.91\cdot10^{-4}\ V^2$ (10% load); $3.17\cdot10^{-3}\ V^2$ (40% load)

The obtained value of the parameter α characterizes the rate of recovery of the supply voltage after a disturbance caused by a change in the propulsion system load. The identified value σ determines the intensity of random fluctuations, and their impact on the system is quantitatively described by the stationary dispersion $Var_{\infty}(U)$.

Thus, experimental oscillographic data allow us to directly link the parameters of the stochastic model with the real operating modes of the UAV.

6. Practical Implications & Discussion

The identification of the drift (α) and diffusion (σ) coefficients provides actionable data for UAV system designers. The results indicate that as the propulsion system moves toward higher power regimes (40% and above), the intensity of stochastic perturbations grows nonlinearly.

Impact on Control Algorithms. The identified $\sigma = 632.0\cdot10^{-3}$ V·s$^{-1/2}$ at 40% load implies that the signal-to-noise ratio (SNR) in the MCU's internal ADC modules may degrade significantly during aggressive maneuvering. This suggests that PID controllers should incorporate load-dependent adaptive filtering. Specifically, the "D" (derivative) term in PID loops, which is highly sensitive to high-frequency noise, could be dynamically dampened when the identified σ exceeds a certain threshold.

Power Distribution Network (PDN) Optimization. Our findings suggest that the SpeedyBee F405 V3 stack, while robust, experiences increased voltage ripple under the load of 2807 1300KV motors. To mitigate the identified fluctuations, developers should consider:

1. Increasing the capacitance of the low-ESR electrolytic capacitors at the battery leads.
2. Implementing additional LC-filters specifically for the 5V/3.3V rails that power the STM32 MCU and the 915 MHz ELRS receiver.

7. Limitations of the Study

While the proposed model and experimental results provide a solid framework for stochastic analysis, several limitations must be acknowledged:

- **Hardware Specificity:** The results are obtained using a 6S1P battery configuration and 1300KV motors. Systems using 4S batteries or higher KV motors for racing (e.g., 2500KV) may exhibit different frequency spectra of noise and different relaxation rates α).
- **Environmental Factors:** The experiments were conducted in a controlled laboratory environment. External factors such as temperature variations (which affect battery internal resistance) and external high-power RF interference were not accounted for in this phase of the study.
- **Linear Approximation:** The matrix C in our model is assumed to be linear. In extreme cases of battery sag or near-critical failure, the system may exhibit nonlinear dynamics that require more complex stochastic modeling beyond the standard Ornstein–Uhlenbeck process.

8. Conclusions

The application of averaging and diffusion approximation to the matrix signal propagation model provides a two-stage theoretical framework for analyzing both the expected dynamics and its stochastic fluctuations in UAV microcontroller systems.

The averaging stage yields a theoretical prediction: when system parameters depend on rapidly varying external perturbations modeled as a Markov process, the limit dynamics are governed by a system with constant (averaged) coefficients. This predicts that the expected trajectory of the signal evolves smoothly — the phase as a linear function of the mean frequency, the amplitude and power decaying as pure exponentials without micro-oscillations. This result holds for the full matrix model and characterizes the deterministic backbone of the system under stochastic loading.

The diffusion approximation stage applies under the balance condition and yields a stochastic differential equation governing fluctuations around the mean trajectory. The drift term captures systematic corrections due to noise correlations, while the diffusion term quantifies the intensity of signal spreading. This stage is directly validated by the experimental oscilloscope measurements of the MCU power supply voltage: the identified relaxation parameter α = 63.0 s^{-1} confirms the OU structure of the voltage fluctuations, and the diffusion coefficients σ and α show that fluctuation intensity grows significantly with propulsion load. These experimentally identified parameters provide a quantitative basis for assessing the reliability of control algorithms and developing adaptive signal processing strategies for UAV systems under stochastic electromagnetic perturbations. Full experimental validation of the averaging stage — including amplitude and phase dynamics — remains a direction for future work.

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