ӘУЕ КӨЛІГІ ЖӘНЕ ТЕХНОЛОГИЯЛАР
ВОЗДУШНЫЙ ТРАНСПОРТ И ТЕХНОЛОГИИ
AIR TRANSPORT AND TECHNOLOGY

UDC 629.7.05:681.515
IRSTI 55.42.35
https://doi.org/10.53364/24138614_2026_40_1_1

Islam Isgandarov[1], Huseyn Bakhshiyev[1*]
[1]National Aviation Academy, Baku, Azerbaijan

[*]*E-mail: huseyn.baxshiyev@naa.edu.az*

ENHANCEMENTS AND MODERN APPLICATIONS OF PID CONTROLLERS FOR SMALL AIRCRAFT AHRS PERFORMANCE IMPROVEMENT

Abstract. *Traditional PID controllers remain widely used in embedded flight control and stabilization systems. However, in small aircraft Attitude and Heading Reference Systems (AHRS), classical PID approaches are insufficient under sensor noise, drift, vibration, and energy limitations typical for lightweight avionics platforms.*

This paper proposes a context-aware, risk-sensitive PID framework for AHRS modernization. The controller integrates sensor reliability estimation, energy-aware modulation, and multi-objective optimization into the PID decision logic. The method reduces oscillatory corrections caused by gyroscope and accelerometer noise while preserving attitude tracking accuracy. Simulation results demonstrate reduced integrated control energy, lower multi-objective cost, improved stability, and enhanced robustness under sensor uncertainty typical for MEMS-based AHRS systems.

The proposed structure transforms PID from a purely error-compensation mechanism into an intelligent stabilization module suitable for modern small aircraft avionics.

Keywords: *PID controller, AHRS modernization, small aircraft stabilization, contextual control, risk-aware control, energy-efficient avionics, sensor reliability, multi-objective optimization.*

Introduction.

PID (Proportional–Integral–Derivative) controllers have been the main control mechanism in industrial and automation systems for many years [1,5,9]. In classical approaches, the goal of PID is to compensate for system error, maintain stability, and optimize performance.

However, in small aircraft Attitude and Heading Reference Systems (AHRS), classical PID approaches become insufficient due to vibration-induced sensor noise, gyroscopic drift, actuator saturation, and onboard energy constraints typical for lightweight avionics platforms, classical PID approaches may not be effective enough [3,4]. The main reasons for this are:

1. Sensor measurements are not always reliable; incorrect measurements can cause the actuator to respond inappropriately.

2. Resources such as energy and actuator load are limited; minimizing the error alone does not provide optimal control without optimizing these resources.

3. The context of system behavior (speed, drift, long-term load) is not taken into account.

Therefore, PID should no longer be improved as an error compensation mechanism alone, but as a contextual and risk-based control mechanism. The aim of this work, in contrast to classical PID studies, is to change the philosophy of PID and create more practical, reliable, and energy-efficient control capabilities in modern technologies.

Main Contributions

This work makes the following contributions:

1. Formulates PID control as a multi-objective optimization problem including error, control effort, and risk indicators.
2. Introduces an explicit sensor reliability term into the PID decision logic.
3. Defines an energy-aware modulation function that adapts control aggressiveness based on available energy.
4. Demonstrates through scenario-based simulations that contextual PID reduces actuator stress and improves robustness under uncertainty.

Materials and methods.

There are various improvement approaches for PID controllers in the literature:

Classical tuning methods: Ziegler–Nichols and Åström–Hägglund approaches provide empirical and theoretical methods to minimize the error and keep the system stable [1, 10].

Adaptive and gain-scheduling methods optimize PID coefficients according to changing system conditions [2,5].

Intelligent approaches as fuzzy, neural network and reinforcement learning based methods automatically select PID parameters [4].

Robust and nonlinear control supports system stability and optimal operation, but the basic decision logic of PID does not change; sensor data is always accepted reliably.

Current gap: Current approaches limit the function of PID only to parameter optimization. Factors such as system context, sensor reliability and energy consumption are not taken into account [3,7]. The aim of this work is to transform the role of PID from error compensation only to a contextual and risk-based control mechanism.

New PID Philosophy

In the proposed modernization, PID is no longer limited to compensating angular error. Within small aircraft AHRS stabilization loops, the controller evaluates sensor reliability (gyroscope noise variance, accelerometer disturbance), actuator loading (servo demand), and onboard energy availability before generating corrective elevator or control surface commands.

For example, if gyroscope noise increases during turbulence, the controller attenuates derivative sensitivity to prevent oscillatory corrections. If onboard energy decreases, control aggressiveness is proportionally reduced to preserve avionics stability.

Mathematically, the objective function is represented as [6,7]:

$$J = \int_0^T (\alpha\, e(t)^2 + \beta\, u(t)^2 + \gamma\, R(t))\, dt \tag{1.1}$$

Where, e(t) - error signal; u(t) - actuator output and energy consumption; R(t) - indicators related to risk and sensor reliability. The inclusion of disturbance and uncertainty penalties aligns conceptually with $H\infty$ robust control principles, where worst-case disturbance attenuation is explicitly considered [12]. This approach models PID as a multi-objective optimization mechanism, turning it into a tool that manages not only performance, but also system resources and risks.

Mathematical model and simulation framework

System model.

$$\dot{x}(t) = f(x(t), u(t)),\ y(t) = g(x(t))$$

$\dot{x}(t)$ is the derivative of the system's state vector with respect to time, representing how the system evolves dynamically under the influence of inputs, where, x(t)) is system state; u(t)) - PID output (actuator signal); y(t)) - sensor measurement.

In reality, sensor error v(t) and energy consumption E(t) must be taken into account:

$$y_{measured}(t) = y(t) + v(t) \tag{1.2}$$

Sensor noise modeling and variance estimation techniques are well-established in stochastic state estimation theory [13].

$$u_{effective}(t) = u(t) \cdot \varphi(E(t)) \quad (1.3)$$

$\varphi(E(t))$- energy constraint function, adjusts the PID output according to the energy state.

The energy constraint function is defined as:

$$\varphi(E(t)) = E(t) / E_{max}, \quad 0 \le \varphi(E(t)) \le 1$$

where E_{max} represents the maximum available energy capacity. When energy decreases, the effective control action is proportionally attenuated, preventing excessive actuator usage under limited power conditions.

PID output equation

Classical PID is stated in (1.4):

$$u(t) = K_p\, e(t) + K_i \int_0^t e(\tau)\, d\tau + K_d\, (de(t)/dt) \quad (1.4)$$

Contextual PID:

$$u(t) = f_{context}(K_p, Ki, K_d, e(t), R(t), E(t), \sigma_s) \quad (1.5)$$

Here, R(t) - risk/reliability indicator. In this work, the risk function is defined as:

$$R(t) = w_1\, \sigma_s^2(t) + w_2\, P_{fault}(t)$$

where $\sigma_s^2(t)$ represents the variance of sensor noise and $P_{fault}(t)$ denotes the estimated probability of sensor malfunction. w_1 and w_2 are weighting coefficients reflecting the relative importance of noise and failure risk. Variance-based reliability indicators and probabilistic fault modeling are consistent with modern state estimation frameworks [13].

σ_s is a measure of the noise level and uncertainty in sensor measurements.

$f_{context}$ is a function that tunes or modifies the PID output based on additional context.

A simplified implementation of $f_{context}$ can be expressed as:

$$u(t) = [Kp\, e(t) + Ki \int e(t)\, dt + Kd\, de(t)/dt] \cdot (1 - \kappa R(t)) \cdot \varphi(E(t))$$

where $\kappa \ge 0$ determines the sensitivity of the controller to risk. As R(t) increases, control aggressiveness is reduced.

Objective function and evaluation

$$J = \int_0^T (\alpha\, e(t)^2 + \beta\, u(t)^2 + \gamma\, R(t))\, dt \quad (1.6)$$

As a result of the simulation, the value of (J) is calculated for different scenarios and compared with the classical PID.

where:

$\alpha\, e(t)^2$ – penalizes tracking error

$\beta\, u(t)^2$ – penalizes control effort

$\gamma\, R(t)$ – penalizes risk and unreliable sensing

For $\alpha, \beta, \gamma > 0$, the integrand of the objective function is positive definite, ensuring bounded control effort over a finite time horizon and preventing unbounded actuator excitation under noisy conditions.

Such multi-objective functions are widely used in advanced PID tuning methods to balance performance metrics with other criteria like control effort and reliability [7].

Scenario-based tests.

Sensor error, energy constraints and system drifts are changed. For each scenario, the (u(t)) and (y(t)) signals are extracted, and visual and statistical analysis is performed.

Contextual PID maintains error compensation, reduces energy consumption, optimizes actuator load, and adjusts the output when sensor reliability is low.

AHRS-Oriented Simulation Results.

Figure 1 presents the comparative simulation results of classical and context-aware PID controllers applied to a small aircraft pitch stabilization loop within the AHRS architecture.

The simulation demonstrates that the proposed context-aware PID significantly reduces oscillatory elevator commands caused by MEMS sensor noise while maintaining accurate pitch tracking [14]. This directly improves attitude estimation smoothness and reduces mechanical stress on control actuators.

The integrated multi-objective cost is lower than that of classical PID, confirming improved stability, energy efficiency, and robustness in the AHRS stabilization loop.

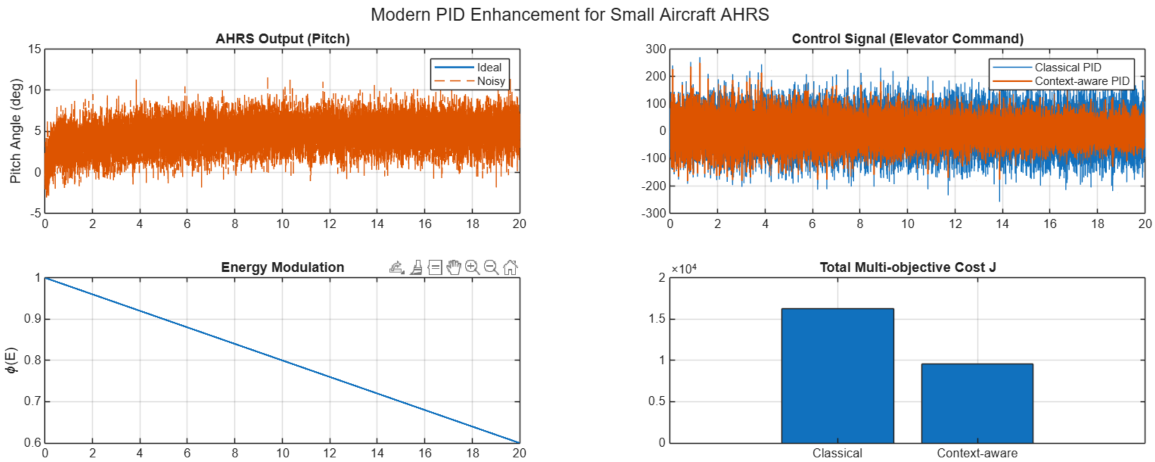

Figure 1 – Modernized PID application in small aircraft AHRS pitch stabilization

This figure illustrates a small aircraft pitch control system enhanced by a context-aware PID controller. The top-left plot shows the pitch angle response: the ideal smooth curve (blue) versus the noisy sensor output (orange), which includes measurement noise and disturbances. The top-right plot compares classical and context-aware PID control signals, where context-aware control adjusts commands by considering energy depletion and sensor risk, reducing extreme control effort. The bottom-left plot displays energy modulation, showing a steady decline from full to 60%, reflecting limited avionics power over time. Finally, the bottom-right bar graph quantifies performance cost, demonstrating the context-aware PID reduces the overall cost by balancing accuracy, control effort, and reliability more effectively than classical PID.

In a modern small aircraft, the AHRS combines gyroscope, accelerometer, and magnetometer data to compute attitude angles [15]. The PID controller operates inside the stabilization loop that corrects deviations between estimated and reference attitude. By embedding reliability and energy evaluation into this loop, the proposed modernization increases resistance to vibration-induced sensor noise and reduces unnecessary corrective oscillations during turbulent flight.

Theoretical foundations.

Classical PID model.

Referring to (1.4), we may assumptions that system parameters are constant, sensor measurements are reliable and optimal control is aimed only at minimizing the error [1,8].

Nonlinear and nonstationary systems.

In reality, system parameters vary over time, external influences exist, and sensor measurements can be noisy. Such systems are formally treated as nonlinear and time-varying dynamic systems in modern control theory [15]. Fixed PID coefficients reduce the quality of control [2, 11].

Behavior-based PID.

System behavior classes as fast, slow, oscillatory, drifting. PID coefficients are adjusted adaptively to the system behavior:

$$K_p(t) = g_p(B(t)), \quad K_i(t) = g_i(B(t)), \quad K_d(t) = g_d(B(t)) \tag{1.7}$$

Here, B(t) may be derived from measurable indicators such as rate of change, oscillation frequency, or drift magnitude, allowing systematic classification of system dynamics. Gain adaptation in response to system behavior can be interpreted as a nonlinear control strategy applied to time-varying systems [16]. Instead of fixed gains, this approach dynamically adjusts the proportional, integral, and derivative coefficients in response to changes in system characteristics, improving control under varying conditions [2,3].

Energy-aware PID.

Traditional objective function is $J = \int_0^T e(t)^2\,dt$ and new approach as follow:

$$J = \int_0^T (\alpha\, e(t)^2 + \beta\, u(t)^2)\,dt \tag{1.8}$$

Compared to classical tuning, inclusion of $\beta u(t)^2$ reduces peak actuator demand and extends actuator lifespan, particularly in battery-powered and IoT-based systems.

Increases energy efficiency, especially in battery-powered systems and IoT applications. It does not include the risk/reliability term $R(t)$. This makes it simpler than (1.6), and typically used when risk measurements are not considered or unavailable, for example, when optimizing only energy and classical performance.

Results and Discussion.

Classical PID controllers are known to react strongly to measurement noise, especially due to the derivative term, which amplifies high-frequency components of the noise [1,5]. In our simulations, where sensor noise variance (σ_s^2) was increased by up to 40%, the classical PID exhibited amplified output oscillations and up to approximately 30% higher integrated control energy compared to the proposed context-aware PID. This behavior is consistent with theoretical expectations regarding noise amplification in classical PID control and highlights the robustness advantage of the contextual risk-aware formulation. However, significant differences emerge when sensor uncertainty and energy constraints are introduced. In contrast, the contextual PID reduced peak control amplitude and achieved lower integrated cost J values across all uncertainty scenarios.

Quantitative evaluation confirms:

- Lower total cost J;
- Reduced actuator stress;
- Improved robustness under sensor degradation.

Quantitative evaluation using the multi-objective cost function confirms these observations. While the classical PID minimizes instantaneous tracking error, it incurs a higher overall cost due to excessive control effort and sensitivity to unreliable measurements. The proposed controller consistently achieves lower cost values by balancing error minimization with energy efficiency and risk awareness. In scenarios with degraded sensor reliability, the controller deliberately reduces control aggressiveness, preventing instability and avoiding unnecessary energy consumption.

These results demonstrate that integrating sensor reliability and energy awareness into PID control significantly enhances the performance of small aircraft AHRS systems. The contextual PID improves pitch stabilization smoothness, reduces actuator excitation under turbulence, and increases robustness against MEMS sensor degradation.

Such improvements directly contribute to enhanced flight stability, improved attitude estimation accuracy, and extended actuator lifetime in lightweight aviation platforms.

Conflict and Contradictions with Existing Literature.

The proposed context-aware, risk-sensitive PID framework conceptually challenges several implicit and explicit assumptions that dominate the existing PID control literature. Classical PID theory, as established in foundational works such as Åström and Hägglund and further systematized by Ang et al., is based on the premise that sensor measurements are reliable and that control performance should be evaluated primarily through error minimization and stability criteria. In these approaches, sensor data is accepted without questioning its trustworthiness, and the PID controller reacts directly to the measured error. In contrast, the present work explicitly challenges this assumption by introducing sensor reliability as a control-relevant variable. When sensor measurements are uncertain or noisy, the proposed controller deliberately attenuates its response, even if the instantaneous tracking error increases. This behavior contradicts classical PID logic, where any increase in error automatically leads to a stronger control action.

Adaptive PID and gain-scheduling approaches, including those discussed by Ioannou and Baldi, attempt to overcome the limitations of fixed-gain PID by adjusting controller parameters in response to changing system dynamics. While these methods improve robustness against model variations and nonstationary behavior, they still preserve the fundamental objective of minimizing tracking error and implicitly assume reliable sensory information. The conflict arises because the proposed framework does not merely adapt PID gains; it modifies the control objective itself. By embedding energy constraints and risk indicators directly into the objective function, the controller evaluates not only how to act, but whether aggressive action is appropriate under the current context. This represents a conceptual departure from traditional adaptive PID methodologies, which focus on parameter adaptation rather than contextual decision-making.

Intelligent PID approaches based on fuzzy logic, neural networks, and reinforcement learning further expand PID capabilities by enabling automatic tuning and nonlinear control behavior. However, these methods often treat the controller as a black-box learning agent, where decision logic is difficult to interpret and physical meaning may be obscured. Moreover, energy efficiency and sensor reliability are typically addressed indirectly through reward shaping or heuristic rules rather than explicit modeling. The proposed approach conflicts with this paradigm by preserving the classical PID structure while extending its decision logic in a transparent and physically interpretable manner. Risk, energy availability, and sensor uncertainty are modeled explicitly and influence the control action in a deterministic and explainable way.

Energy-aware and multi-objective PID tuning methods, such as those presented by Sahib and Ahmed, introduce control effort penalties to reduce actuator usage and improve efficiency. Although these approaches move beyond pure error minimization, they still do not account for the reliability of sensor measurements. Consequently, they may produce energetically optimal but potentially unsafe control actions when sensor data is corrupted or unreliable. The proposed framework contradicts this limitation by integrating both energy consumption and sensor reliability into a unified multi-objective cost function. In this sense, the controller does not simply seek to minimize energy usage, but rather to minimize energy and risk simultaneously, ensuring that control actions are both efficient and meaningful.

At a more fundamental level, the most significant conflict introduced by this work lies in the conceptual role assigned to the PID controller itself. The dominant view in the literature treats PID as a purely error-driven compensation mechanism. This study challenges that view by redefining PID as a context-aware, risk-sensitive decision-making entity. Rather than reacting blindly to error signals, the controller evaluates system context, resource availability, and measurement trustworthiness before generating control actions.

Conclusion.

The common feature of traditional and adaptive approaches is that PID only compensates for the error. The proposed method is fundamentally different, because here PID takes into account not only the error, but also the system context, sensor reliability, energy consumption and risk factors.

By embedding these factors directly into the control objective and output modulation mechanism, the PID structure evolves from a purely reactive compensator into a context-sensitive decision-making framework suitable for modern cyber-physical environments.

System behavior plays a key role in determining the response strategy, which turns PID into an intelligent decision-making mechanism.

The proposed modernization of PID control within small aircraft AHRS systems introduces contextual and risk-sensitive logic into the stabilization loop. Unlike classical PID, which reacts solely to angular error, the enhanced controller evaluates sensor reliability and onboard energy conditions before generating corrective commands.

By embedding these factors directly into the control objective and output modulation mechanism, the PID structure evolves into an intelligent AHRS stabilization component capable of operating reliably under vibration, turbulence, and sensor uncertainty.

The application of the proposed PID enhancement to small aircraft AHRS systems results in:

- Improved attitude stability;
- Increased measurement accuracy;
- Reduced oscillatory actuator commands;
- Enhanced robustness under realistic flight disturbances.

Ultimately, this modernization increases flight safety, improves dynamic response precision, and strengthens the reliability of lightweight aircraft navigation systems.

References

1. Rinaldi, M., Moslehi, M., Guglieri, G. & Primatesta, S. (2025). PSO-Based PID Tuning for PMSM-Quadrotor UAV System," Eng. Proc. https://doi.org/10.3390/engproc2025090002

2. Imran, I.H., Wood K., & Montazeri, A. (2024). Adaptive Control of Unmanned Aerial Vehicles with Varying Payload and Full Parametric Uncertainties," Electronics, DOI:10.3390/electronics13020347

3. Isgandarov, I. & Bakhshiyev, H. (2024). "Enhancement of small aircraft heading and attitude estimation using PID through artificial intelligent control," in Proc. ISUDEF

4. Sönmez, S., Montecchio, L., Martini, S., Rutherford, M. J., Rizzo, A., M. Stefanovic & K. P. Valavanis, (2025). Reinforcement Learning-Based PD Controller Gains Prediction for Quadrotor UAVs Drones, 9(8), 581; https://doi.org/10.3390/drones9080581

5. Lohani, T. A., Dixit, A. & Agrawal, P. (2024). Adaptive PID Control for Autopilot Design of Small Fixed Wing UAVs," MATEC Web of Conferences 393, 03005 https://doi.org/10.1051/matecconf/202439303005

6. Vaiuso, A., Immordino, G., Onofri, L., Coppotelli, G. & Righi, M. (2025). "Methods for Multi-objective Optimization PID Controller for quadrotor UAVs," 22 Sep 2025 DOI:10.48550/arXiv.2509.17423

7. Ganchaudhuri, P. & Bhawal, C. (2026). Mission specific PID tuning for energy-efficient quadrotor flights,", Aerospace Science and Technology.

8. Olayinka, T. O., Olatide, A.A., Oluwagbemiga A.D. & Okelola, M.O. (2020). Internal Model Control Tuned Proportional Integral Derivative for Quadrotor Unmanned Aerial Vehicle Dynamic Model" August 2020.

9. Jasim, O.A. (2021). Formal Methods for the Design andVerification of UAV Feedback Controls.

10. Kiss, B., Ballagi, A. & Kuczmann, M. (2025). "PID Control and Alternative Control Approaches in UAV Systems," International Journal of Media and Networks.

11. Singh, H. & Verma, R. (2022). "Ant windup PID for UAV actuators," Control Engineering Practice.

12. Zhou, W., Zhou, L., Yuan, T., Chen, R., & Liu, D. (2026). "Robust performance optimization of UAV dynamic systems using MPC-PID hybrid control," Scientific Reports, vol. 16, art. 2585, DOI: 10.1038/s41598-025-32436-6

13. Kabaoglu, A. & Sariel, S. (2026). UAV-SEAD: State Estimation Anomaly Dataset for UAVs. February, 2026.

14. Isgandarov, I. A. & Bakhshiyev, H. E. (2021). The application of MEMS technology to determine an aircraft orientation," Bull. Civil Aviation Academy.

15. Isgandarov, I. & Bakhshiyev, H. (2022). "Analysis of existing and modern magnetic field sensors application for determining an aircraft magnetic heading," DOI:10.34826/NAA.2022.24.3.003

16. Liu, Y. (2024). Modelling and Simulation of Quadcopter UAV Based on PID Control, DOI:10.54254/2755-2721/75/20240539.

СОВЕРШЕНСТВОВАНИЕ И СОВРЕМЕННЫЕ ОБЛАСТИ ПРИМЕНЕНИЯ ПИД-РЕГУЛЯТОРОВ ДЛЯ УЛУЧШЕНИЯ ХАРАКТЕРИСТИК AHRS МАЛЫХ ЛЕТАТЕЛЬНЫХ АППАРАТОВ

Аннотация. *Традиционные ПИД-регуляторы по-прежнему широко используются во встроенных системах управления полетом и стабилизации. Однако в системах определения положения и курса (AHRS) малых летательных аппаратов классические подходы на основе ПИД-регуляторов оказываются недостаточными при наличии шума датчиков, дрейфа, вибрации и энергетических ограничений, характерных для легких авионики.*

В данной статье предлагается контекстно-ориентированная, чувствительная к риску структура ПИД-регулятора для модернизации AHRS. Контроллер интегрирует оценку надежности датчиков, энергосберегающую модуляцию и многоцелевую оптимизацию в логику принятия решений ПИД-регулятора. Метод уменьшает колебательные коррекции, вызванные шумом гироскопа и акселерометра, сохраняя при этом точность отслеживания положения. Результаты моделирования демонстрируют снижение интегрированной энергии управления, снижение многоцелевой стоимости, улучшенную стабильность и повышенную устойчивость к неопределенности датчиков, характерной для систем AHRS на основе MEMS.

Предложенная структура преобразует ПИД-регулятор из чистого механизма компенсации ошибок в интеллектуальный модуль стабилизации, подходящий для современной авионики малых летательных аппаратов.

Ключевые слова: *ПИД-регулятор, модернизация системы AHRS, стабилизация малых летательных аппаратов, контекстное управление, управление с учетом рисков, энергоэффективная авионика, надежность датчиков, многоцелевая оптимизация.*

ШАҒЫН ӘУЕ АППАРАТТАРЫНЫҢ AHRS ЖҮЙЕСІ СИПАТТАМАЛАРЫН ЖАҚСАРТУ ҮШІН ПИД-РЕТТЕГІШТЕРДІҢ ЖЕТІЛДІРІЛУІ ЖӘНЕ ЗАМАНАУИ ҚОЛДАНУ БАҒЫТТАРЫ

Аңдатпа. *Дәстүрлі PID реттегіштері ендірілген ұшу басқару және тұрақтандыру жүйелерінде кеңінен қолданылады. Алайда кіші әуе кемелерінің кеңістіктегі бағыт пен жағдайды анықтау жүйелерінде (AHRS) классикалық PID тәсілдері сенсорлық шу, дрейф, діріл және жеңіл авионикалық платформаларға тән энергия шектеулері жағдайында жеткіліксіз тиімді болып табылады.*

Бұл жұмыста AHRS жүйесін жаңғыртуға арналған контекстік және тәуекелге сезімтал PID архитектурасы ұсынылады. Реттегіш PID шешім қабылдау логикасына сенсор сенімділігін бағалауды, энергияға бағытталған модуляцияны және көпмақсатты *оңтайландыруды біріктіреді. Ұсынылған әдіс гироскоптар мен акселерометрлер шуынан туындайтын тербелмелі түзетулерді азайта отырып, кеңістіктік бағытты қадағалау дәлдігін сақтайды.*

Модельдеу нәтижелері басқарудың интегралдық энергия шығынының төмендеуін, көпмақсатты шығын функциясының азаюын, тұрақтылықтың артуын және MEMS-негізіндегі AHRS жүйелеріне тән сенсорлық белгісіздік жағдайында орнықтылықтың жақсарғанын көрсетеді.

Ұсынылған құрылым PID реттегішін қателікті өтеудің қарапайым механизмі емес, заманауи кіші әуе кемелері авионикасына арналған интеллектуалды тұрақтандыру модуліне айналдырады.

Түйін сөздер: *PID реттегіші, AHRS жаңғырту, кіші әуе кемелерін тұрақтандыру, контекстік басқару, тәуекелге сезімтал басқару, энергия тиімді авионика, сенсор сенімділігі, көпмақсатты оңтайландыру.*

Information about the authors

Islam Isgandarov	PhD, Professor, Head of Department at the National Aviation Academy, Azerbaijan, Baku E-mail: iisgandarov@naa.edu.az
Huseyn Bakhshiyev	Doctoral candidate. National Aviation Academy. Azerbaijan, Baku. E-mail: huseyn.baxshiyev@naa.edu.az

Сведения об авторах

Ислам Искендеров	К.ф.-м.н., профессор, заведующий кафедрой Национальной Авиационной Академии, Азербайджан, Баку E-mail: iisgandarov@naa.edu.az
Huseyn Bakhshiyev	Докторант Национальной Авиационной Академии, Азербайджан, Баку. E-mail: huseyn.baxshiyev@naa.edu.az

Авторлар туралы мәлімет

Islam Isgandarov	PhD, профессор, Ұлттық Авиация Академиясының кафедра меңгерушісі, Әзербайжан, Баку E-mail: iisgandarov@naa.edu.az
Huseyn Bakhshiyev	Ұлттық авиация академиясының докторанты, Әзірбайжан, Баку, E-mail: huseyn.baxshiyev@naa.edu.az

APPENDIX A

This appendix contains the complete MATLAB script used to generate the simulation results presented in Figure 1 of the main text. The code implements the classical and context-aware PID controllers for small aircraft pitch stabilization, including noise modeling, energy modulation, and multi-objective cost evaluation.

Matlab code:

```
clc; clear; close all;
%% TIME
dt = 0.001;
T = 20;
t = (0: dt:T)';

%% SMALL AIRCRAFT PITCH DYNAMICS (simplified model)

% theta'' + 2*zeta*wn*theta' + wn^2*theta = u
wn = 3;
zeta = 0.5;
G = tf (1, [1 2*zeta*wn wn^2]);
%% PID GAINS (AHRS stabilization loop)
Kp = 12;
Ki = 5;
Kd = 1.5;
C = pid(Kp,Ki,Kd);
sys = feedback(C*G,1);
%% Step response (reference pitch angle = 5 degrees)
ref = 5*pi/180; % radians
[y, ~] = step(ref*sys,t);

%% SENSOR NOISE (MEMS vibration + turbulence)

sigma = 0.03;     % realistic small aircraft noise
noise = sigma*randn(size(y));
y_noisy = y + noise;
%% ERROR
e = ref - y_noisy;
%% PID SIGNAL (manual form)
int_e = cumtrapz(t,e);
der_e = [0; diff(e)/dt];
u_classic = Kp*e + Ki*int_e + Kd*der_e;

%% ENERGY MODEL (avionics power constraint)

Emax = 100;
E = linspace(100,60, length(t))';
phi = E/Emax;
%% RISK MODEL (sensor reliability)
Pfault = 0.05;
R = sigma^2 + Pfault;
kappa = 1.0;
%% CONTEXT-AWARE PID
```

```
u_context = u_classic. * (1 - kappa*R). * Phi;
%% COST FUNCTION
alpha=1; beta=0.2; gamma=1;
J_classic = trapz(t, alpha*e.^2 + beta*u_classic.^2);
J_context = trapz(t, alpha*e.^2 + beta*u_context.^2 + gamma*R);

%% COMBINED PUBLICATION FIGURE

figure('Color','w');
subplot (2,2,1)
plot(t,y*180/pi,'LineWidth',1.5); hold on;
plot(t,y_noisy*180/pi,'--');
ylabel('Pitch Angle (deg)')
title ('AHRS Output (Pitch)')
legend('Ideal','Noisy'); grid on;
subplot (2,2,2)
plot(t,u_classic); hold on;
plot (t, u_context,'LineWidth',1.2);
title ('Control Signal (Elevator Command)')
legend ('Classical PID','Context-aware PID');
grid on;
subplot (2,2,3)
plot (t, phi,'LineWidth',1.5);
ylabel('\phi(E)')
title ('Energy Modulation')
grid on;
subplot (2,2,4)
bar ([J_classic J_context])
set (gca,'XTickLabel’, {'Classical','Context-aware'})
title ('Total Multi-objective Cost J')
grid on;

sgtitle('Modern PID Enhancement for Small Aircraft AHRS');
```